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An effective two-stage stochastic multi-trip location-transportation model with social concerns in relief supply chains

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Abstract

The distribution of emergency aid from warehouses to relief centers to satisfy the needs of the victims in the aftermath of a disaster is a complex problem because it requires a rapid response to human suffering when resources are scarce amidst great uncertainty. In order to provide an effective response and use resources efficiently, this paper presents a novel model to optimize location, transportation, and fleet sizing decisions. In contrast with existing models, vehicles can be reused for multiple trips within micro-periods (blocks of hours) and/or over periods (days). Uncertainty regarding demand, incoming supply, and availability of routes is modelled via a finite set of scenarios, using two-stage stochastic programs. 'Deprivation costs' are used to represent social concerns and minimized via two objective functions. Mathematical programming based heuristics are devised to enable good-quality solutions within reasonable computing time. Experimental results based on data from the disastrous 2011 floods and landslides in the Serrana Region of Rio de Janeiro, Brazil, show that the model's novel characteristics help get aid faster to victims and naturally enforce fairness in its distribution to disaster areas in a humanitarian spirit.

Keywords:
OR in disaster relief, Location-transportation and fleet sizing, multiple trips, deprivation costs, MIP heuristics

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1. Introduction

Brazil's *National System for Protection and Civil Defense* (SINPDEC) manages the country's emergency preparedness and response to severe disasters. Its main role is to reduce the impact of disasters in vulnerable communities, and so mitigate human suffering and preserve the population's well-being (Valencio, 2010). The increasing number of affected people and the economic damage caused by disasters in recent years have highlighted the difficulty that organizations such as SINPDEC face in responding effectively to the various types of disasters that plague Brazil. For example, in one of the country's worst socio-environmental disasters, the so-called Megadisaster of the Serrana region of Rio de Janeiro state in 2011, floods and landslides claimed more than 1,000 lives and left around 30,000 people displaced and homeless. Experts assess that this scale of impact was due to the lack of well-structured contingency plans and coordination problems between the different bodies involved in the initial response phase.

Clearly, part of the problem is due to the unpredictability and complexity of such disaster events. The needs of victims are difficult to forecast and can arise with little or no warning. There is a mismatch between supply and demand, as the latter may depend on the uncertain behavior of in-kind donations (Barber, 2012). Transport links may be poorly mapped, only partially functional, or destroyed. Transport to distribute relief supplies may not be readily available. Moreno et al. (2016) also points out that "... multiple agencies may be trying to satisfy the same perceived need in an uncoordinated manner, just as commercial competitors do, but with little prior information about needs, resulting in over and under supply with consequent human suffering and avoidable deaths". These problems can be even more challenging in developing economies where relief resources are usually scarce and thus not sufficient to fulfill people's needs in the aftermath of a disaster.

This paper handles this complexity by proposing a novel integrated approach to improve distribution logistics in disaster situations under uncertainty. Our optimization model integrates key preparedness and response activities for an effective disaster management, such as location of relief centers and transportation of emergency aid, which includes fleet-sizing decisions in both pre- and post-disaster phases. Each single vehicle is allowed to make several journeys within the period and over the time horizon without restricting the period's length, economizing overall resources. Typical uncertainty data such as victims' needs, incoming supplies, and route availability is modeled via a set of discrete scenarios and incorporated in the optimization model following the two-stage stochastic programming paradigm.

Furthermore, we propose two approaches to take into account social concerns during relief operations, both based on the concept of deprivation costs that victims incur due to the lack of emergency aid. One approach prioritizes the minimization of deprivation costs over logistics costs, while the other, minimizes logistics and deprivation costs jointly in a single objective function as (Holguín-Veras et al., 2013). Overall results in this paper show that it is possible to mitigate human suffering via a more effective demand fulfillment policy based on deprivation costs in either mono- or bi-objective fashion. In fact, the main findings clearly show that deprivation costs help to provide a more equitable solution amongst the different affected areas and, simultaneously, providing good service levels as much as possible given the scarcity of resources.

The computational results are analyzed with data instances based on the disastrous 2011 floods and landslides in the Serrana Region of Rio de Janeiro, Brazil. We also devised three heuristic strategies to provide good-quality solutions within reasonable elapsed times for our practical instances: a fix-and-optimize heuristic; a two-step heuristic based on an approximate linear programming model; and a hybrid heuristic that combines the fix-and-optimize and the two-step heuristics. Even though developed with reference to a particular Brazilian case, the numerical results have general relevance for the efficient management of such humanitarian supply chains over a myriad of sudden-onset disasters.

The rest of the paper is organized as follows. Section 2 presents the literature review. Section 3 describes the problem and presents the mathematical model. Section 4 develops the solution methods. Section 5 discusses the computational results. Finally, Section 6 presents the final remarks and future research.

2. Literature review

This paper's literature review focuses on integrated disaster logistics models with multiple trips and deprivation costs, looking at three streams. The first stream (i) concerns recent modelling approaches for integrating distribution, fleet sizing and/or location decisions. The second stream (ii) focuses on how existing approaches have incorporated partial multiple trips. Finally, the third stream (iii) reviews the few models with deprivation costs. The key papers in each category are exhibited in Table 1, which summarizes the main characteristics, decisions, and objective functions of their corresponding optimization approaches, showing their main differences with this paper.

Most studies that developed integrated models for coordinating preparedness and response activities in humanitarian logistics focused on multi-period settings. However, most multi-period models overlooked the uncertainty about the number of affected people and their needs (Yi and Ozdamar, 2007; Afshar and Haghani, 2012; Lin et al., 2012; Vanajakumari et al., 2016). Recognizing the inherent uncertainty in disaster operations, such as the needs of victims, route availability, supplies, and shipping time, various authors have proposed two-stage stochastic programming models, often representing pre-disaster preparedness as first-stage decisions and post-disaster response as second-stage decisions (Salmerón and Apte, 2010; Mete and Zabinsky, 2010; Ahmadi et al., 2015; Rath et al., 2016).

A few papers have attempted to handle multiperiod and stochastic issues in a scenario-based, two-stage paradigm (Bozorgi-Amiri and Khorsi, 2016; Moreno et al., 2016). Fleet (re)sizing is an important recourse decision to hedge against severe uncertainty in post-disaster situations, but this option was adopted only in Moreno et al. (2016). However, in these studies there is still potential to save overall resources by considering the option of reusing the vehicle fleet over the time horizon and within each period, respectively. Note that, although many papers have considered reusing vehicles, with exception of Moreno et al. (2016), none have explicitly discussed this issue nor its benefits in relief distribution.

In this paper, we propose to define the concept of the "partial multi-trip" when vehicles are assumed to be used only once by each period over the time horizon or several times within a period, but without exceeding the period's length. Perhaps surprisingly, only a few papers permit the (re)utilization of vehicles for partial multiple trips within fleet sizing decisions. Two cases are considered: (i) partial multiple trips over the time horizon; or (ii) partial multiple trips within each time period.

In case (i), travel times are assumed to be multiples of the period length. For example, day-long periods lead to travel times of 1 day, 2 days, etc. This approach is not accurate when travel times are much shorter than a period. If, for example, a travel time last 2 hours and the period length is a day, then during the 22 subsequent hours the vehicle is considered "not available" and cannot be used again until the next day. This limited option of reusing vehicles featured in Ozdamar et al. (2004); Yi and Kumar (2007); Yi and Ozdamar (2007); Afshar and Haghani (2012) and Pérez-Rodríguez and Holguín-Veras (2015). While Ozdamar et al. (2004) minimized only the unsatisfied demand, Yi and Kumar (2007) used a weighted-sum function of unmet demand and untreated wounded victims and Pérez-Rodríguez and Holguín-Veras (2015) considered "social costs" via a single objective function composed of logistics and deprivation costs.

In case (ii), vehicles can be reused within the same time period to perform more than one trip. This approach is recent and seems to be more efficient than case (i), but travel times are assumed to be shorter than a period's length and departures in one period cannot arrive in subsequent periods. This case includes integrated models with facility location (Moreno et al., 2016; Bastian et al., 2016; Bozorgi-Amiri and Khorsi, 2016) and without (Lin et al., 2011; Rivera-Royero et al., 2016; Ferrer et al., 2016). The multi-objective deterministic model by Lin et al. (2011) distributes prioritized aid, minimizing unmet demand, logistics costs, and differences in the satisfaction rate between affected areas. Ferrer et al. (2016) addressed last-mile distribution under uncertain conditions using a deterministic model and a multi-criteria metaheuristic approach. Rivera-Royero et al. (2016) minimizes a deprivation cost to mitigate unmet demand in a post-disaster situation, as discussed next. All the aforementioned papers did not discuss the useful impact of performing the existing two types of multiple trips towards to save overall resources. Here, we explicitly show that allowing a vehicle to make several journeys within the period and over the time horizon without restricting the period's length helps to save overall resources.

Recent years have seen an emphasis on addressing human suffering in humanitarian logistics. Holguín-Veras et al. (2013) distinguished between social costs (deprivation plus logistics costs) and other objectives while a later paper (Holguín-Veras et al., 2016) discussed how to estimate deprivation functions. Most research has considered deprivation costs within relief distribution models, such as Pérez-Rodríguez and Holguín-Veras (2015) and Rivera-Royero et al. (2016) who both integrate distribution of supplies and fleet sizing with inventory allocation decisions, but without explicitly considering facility location. In particular, Pérez-Rodríguez and Holguín-Veras (2015) incorporated social costs as a sum of logistics and deprivation costs in mixed-integer non-linear programming models in which an exponential function accounts for the deprivation times for each demand node and emergency aid. Non-linearity limits the size of solvable instances, so heuristic approaches are used to solve simpler versions of the model. In contrast, Rivera-Royero et al. (2016) proposed a mixed-integer linear programming model to approximate the exponential nature of the deprivation cost. A linear deprivation function dependent on the number of time periods is used to account for the deprivation time. The approximation can be improved by reducing the planning periods, but it assumes that demands arise only once, at the beginning of the time horizon. This is often an unrealistic assumption given that victims' needs typically arise in any moment during the timeline of the disaster.

From a different perspective, Huang et al. (2015) used three objectives related to humanitarian principles: lifesaving utility, delay cost, and equity. The lifesaving utility is the preference of affected people regarding the emergency commodity. The delay cost (deprivation cost) represents the effect of not receiving the relief item, reflecting the human suffering caused. Finally, the equity measure aims to minimize unfairness of delivery between affected areas. Different to most studies, the deprivation function is a linear mapping of the deprivation time, so that the shortage effect does not increase exponentially, as it does in Holguín-Veras et al. (2013).

Pradhananga et al. (2016) presented a two-stage stochastic programming model to integrate resource allocation and distribution in pre-disaster planning over a static horizon, assuming too that demands arise only at the beginning of the time horizon. Location, prepositioning, and procurement are decided in the first-stage, and procurement and distribution of supplies in the second-stage. Post-disaster costs include logistics and exponential deprivation costs. However, the resulting problem is still linear because deprivation times are evaluated according to pre-determined conditions to make them dependent only on certain distance parameters.

Notice that the inclusion of deprivation costs in humanitarian logistics is still scarce. Most studies made strong model assumptions attempting to handle deprivation costs in a tractable fashion. For example, the assumption that demands arise only once at the beginning of the time horizon (Rivera-Royero et al., 2016; Pradhananga et al., 2016) is not directly applicable to the complex disaster considered in this work (floods and landslides), because relief distribution must be performed when large amounts of demands are still occurring (randomly) over a time horizon of days or weeks. In addition, the linear deprivation function proposed by Huang et al. (2015) overlooks the typical (exponential) behavior of being deprived from critical supplies. In fact, Holguín-Veras et al. (2016) concluded that deprivation cost functions are better fitted via exponential functions. Pérez-Rodríguez and Holguín-Veras (2015); Rivera-Royero et al. (2016); Huang et al. (2015) also over-simplified their problems by ignoring the uncertainty which is clearly present in practice.

Motivated by several issues not previous researched, this paper develops a novel approach for relief distribution in a multi-period, multi-modal, and multi-commodity context under uncertainty that combines key decisions, such as location of relief centers, distribution of emergency commodities, and fleet sizing in both stages. Uncertainty in incoming supplies, proportion of usable commodities, demand, and availability of routes is handled via a two-stage scenario-based approach that is illustrated using real information on floods and landslides disasters in Rio de Janeiro, Brazil, from 1966 to 2013. In summary, our paper's innovative contributions are as follows:

- We use two different time scales, for example days and hours, to model deprivations costs, while preserving the inherent exponential nature of human suffering, in contrast to the linear deprivation cost function of Huang et al. (2015). Thus our mathematical model remains a mixed-integer linear program, differently from the non-linear model of Pérez-Rodríguez and Holguín-Veras (2015).
- Our model is more realistic than many existing studies, for the following reasons: (i) Demands can arise in any time period during the timeline of the disaster, thus the so-called inter-temporal effects in distribution relief are properly assessed. In effect, larger deliveries to a relief center can be strategically used in our context to satisfy immediate and future people's needs when emergency aid can be stored from one period to another. On the contrary, Rivera-Royero et al. (2016) and Pradhananga et al. (2016) assume that demands arise only at the beginning of the time horizon. (ii) Our proposed deprivation function takes into account the total number of people affected by the shortage of a given emergency commodity. This is important as deliveries are commonly "family-oriented" in disaster situations, not oriented to a single person. (iii) Vehicles are allowed to perform total multiple trips anytime during the time horizon. These three features have not been taken into account before in a dynamic stochastic environment.
- Finally, for the first time, social concerns are considered via a hierarchical bi-objective function that prioritizes saving lives as fast as possible, while efficiency takes secondary importance'. Moreover, a mono-objective version of the problem evaluate the most suitable approach in disaster management.

Table 1: Summary of the main features, decisions, and objective functions supported by the existing models in the humanitarian logistics literature whose contribution is related to stream (i), (ii), or (iii).

Reference	Stream[1]	Model features: Approach[2]	Multi-period	Multi-product	Multi-modal	Travel time	Multi-trip[3]	Decisions: Location	Fleet sizing[4]	Tranportation	Inventory level	Other decision[5]	Objective function	↓ Unmet demand	↑ Served demand	↓ Response time	↓ Logistic costs	↓ Deprivation costs	Other objetives[6]
Ozdamar et al. (2004)	2	MIP	✓	✓	✓	✓	(i)		Det	✓			Mono	✓					
Yi and Ozdamar (2007)	1,2	MIP	✓	✓	✓	✓	(i)	✓	Det	✓		✓	Mono	✓					✓
Yi and Kumar (2007)	2	MIP	✓	✓	✓	✓	(i)		Det	✓		✓	Mono	✓					✓
Salmerón and Apte (2010)	1	SMIP			✓	✓		✓	Second	✓		✓	Multi	✓					✓
Mete and Zabinsky (2010)	1	SMIP		✓	✓	✓		✓	Second	✓	✓		Mono	✓		✓	✓		
Lin et al. (2011)	2	MIP	✓	✓	✓	✓	(ii)		Det	✓			Multi	✓			✓		✓
Afshar and Haghani (2012)	1,2	MIP	✓	✓	✓	✓	(i)	✓	Det	✓			Mono	✓					
Lin et al. (2012)	1	MIP	✓	✓		✓		✓	Det	✓			Mono	✓			✓		✓
Ahmadi et al. (2015)	1	SMIP		✓		✓		✓	First	✓			Mono	✓		✓	✓		
Pérez-Rodríguez and Holguín-Veras (2015)	2,3	MINLP	✓	✓	✓	✓	(i)		Det	✓	✓		Mono				✓	Non-linear	
Huang et al. (2015)	3	MIQP	✓							✓			Mono				✓	Linear	✓
Rath et al. (2016)	1	SMIP			✓	✓		✓	First	✓		✓	Multi		✓		✓		
Bozorgi-Amiri and Khorsi (2016)	1,2	SMIP	✓	✓	✓	✓	(ii)	✓	Second	✓	✓	✓	Multi			✓	✓		✓
Vanajakumari et al. (2016)	1	MIP	✓	✓	✓	✓		✓	Det	✓	✓		Mono	✓			✓		✓
Bastian et al. (2016)	2	SMIP			✓	✓	(ii)	✓	Second	✓	✓	✓	Multi		✓	✓	✓		
Rivera-Royero et al. (2016)	2,3	MIP	✓	✓	✓	✓	(ii)		Det	✓	✓		Mono					Non-linear	
Moreno et al. (2016)	1,2	SMIP	✓	✓	✓	✓	(ii)	✓	First, second	✓	✓	✓	Mono	✓			✓		
Pradhananga et al. (2016)	3	SMIP		✓				✓		✓	✓	✓	Mono				✓	Non-linear	
Ferrer et al. (2016)	2	MIP			✓	✓	(ii)		Det	✓			Multi			✓	✓		✓
This paper	1,2,3	SMIP	✓	✓	✓	✓	(i), (ii)	✓	First, second	✓	✓	✓	Multi				✓	Non-linear	

[1] Stream 1: models for integrating location, transportation, and/or fleet sizing decisions; Stream 2: models that incorporate partial multiple trips; Stream 3: models with deprivation costs.
[2] MIP: Mixed Integer Programming; MIQP: Mixed Integer Quadratic Programming; MINLP: Mixed Integer Nonlinear Programming; SMIP: Stochastic Mixed Integer Programming.
[3] Multiple trips: (i) over the time horizon; (ii) within each time period.
[4] Det: fleet-sizing is performed in a deterministic fashion; First: fleet-sizing is performed in the first-stage of a two-stage stochastic model; Second: fleet-sizing is performed in the second-stage of a two-stage stochastic model.
[5] Evacuation of victims; allocation of demand; design of routes; expansion of capacity; definition of budget; purchase/procurement of commodities.
[6] Minimize: unmet wounded victims, expected casualties, unfairness of services among nodes, maximum amount of unsatisfied demand among nodes, unused inventories. Maximize: equity, reliability, security.

3. Problem description and mathematical modeling

We propose to devise a mathematical tool to support typical logistics activities that must be effectively carried out within the disaster life cycle to fulfill victims' needs in the aftermath of a disaster event. Based on Brazilian practices and reality, we assume that humanitarian assistance is composed of different types of emergency commodities, which are usually in-kind donations raised after disaster strikes. Our goal is to provide an optimized plan to ensure that such goods will be distributed at the right time and place to mitigate human suffering as much as possible. For this purpose, we present a location-transportation problem that is particularly appealing to handle recurrent weather-related hazards, such as floods and landslides, which can be *relatively* predictable events in terms of timing in some geographical areas, in the sense that they are mostly associated with certain climatological triggering events that usually occur in specific seasons. However, even such disaster events may lead to a rather uncertain post-disaster situation due to the unknown exact nature and magnitude of the hazard. As a consequence, victims' needs, incoming supplies, and overall physical damages are rarely precisely known before disaster strikes.

To take into account the aforementioned uncertainty, we invoke a two-stage stochastic programming paradigm in which preparedness (pre-disaster) decisions are taken in the first-stage, typically 1 to 4 weeks before disaster strikes, with partial information on the disaster impact and effects. In practical settings, such information can be given by forecast or early-warning systems, for example. The response (post-disaster) decisions are thus performed in the second-stage. Following stochastic programming theory, victims needs, incoming supplies (in-kind donations), arc availability (undamaged roads), and the proportion of usable inventory at relief centers (RCs) are modeled as random variables over a probability space (Ξ, Π), in which Ξ is the support of each scenario ξ and Π is a probability measure such that $\Pi(\xi \in \Xi) = 1$ almost surely.

In the first-stage, we plan two logistics activities: the pre-selection of a set of relief centers (RCs) that will be used by displaced and homeless people seeking humanitarian assistance; and the definition of the fleet of vehicles in terms of type and number that should be deployed at the existing depots to carry the emergency commodities to the pre-selected RCs. We assume that depots are already located in non-vulnerable areas based on the fact that warehousing is usually a long-term decision, and thus beyond the scope of this paper's goals. However, we must define which RC will be established to meet the needs of the affected areas in an attempt to avoid wasting time finding/setting appropriate facilities after a disaster, which is usually more time-consuming, considering the chaotic post-disaster situation (socioeconomic vulnerabilities, network damages, etc.). Moreover, priority should be given to the relief assistance in the first few hours after a disaster strikes to mitigate human suffering and avoid deaths.

As the relief centers are usually existing facilities that operate as public schools, churches, and offices, among others, they do not necessarily have suitable infrastructure to temporarily accommodate supplies. For this reason, we consider a storage capacity given in volume of goods and a per product capacity to indicate, for example, that some RCs might not have the required quality of refrigeration to store medical products. As a consequence, such relief aid should not be sent to that RC. It is worth noting that RCs can be located in vulnerable areas. The fixed cost for opening and operating relief centers are associated with minor arrangements.

The fleet of vehicles can be composed of different transportation modes in order to reach collapsed regions. They must be rapidly deployed as soon as disaster strikes, and possibly be located at the depots nearer the pre-selected RCs. It is assumed that vehicles are procured via public tender and there are only a limited number of them in the first-stage. Commodities can be heavy or bulky, so vehicle loading is limited by both weight and volume capacities.

In the second-stage, we basically need to plan how to fulfill victims' needs for each potential disaster scenario, which involves performing transportation and relief distribution activities, and which also includes inventory management at depots and RCs. All the response decisions are taken over a finite time horizon divided into day-long time periods which are further divided into micro-periods of hours or blocks of hours. Some decisions must be taken by period and other ones by micro-period. Commonly, after the disaster strikes, incoming supplies, mainly in the form of in-kind donations, will randomly arrive at some existing depots. From the depots, these relief supplies are sent to the already established RCs using the available vehicles through the undamaged arcs in order to fulfill the victims' needs as soon as possible. Thus, the recourse decisions include the flow of commodities and vehicles along the routes by micro-period. The vehicles defined in the pre-disaster may be not enough to complete the distribution of commodities, so additional vehicles can be procured by period in the second-stage, and via the spot market at much higher prices. We assumed that the vehicle's operation is intrinsically associated with the depot where it was first procured. Therefore, a given vehicle's route starts at a given depot, visits a relief center to unload, and returns to the same depot. However, this assumption could be extended to more general settings where the procured vehicles can be managed by any other depot or relief agency.

Based on practical disaster situations, this paper assumes that relief centers have to meet large quantities of demand and, for this reason, the vehicles used to transport the commodities usually unload all their truckload at the same relief center. Furthermore, in most cases, the vehicles available to perform the relief distribution have a small capacity in comparison to the quantity of emergency commodities that need to be shipped. For this reason, we do not consider the possibility that a vehicle visits more than one RC before returning to its depot. Travel times on route (i, j) and (j, i) are the same. We assume an upper bound for the total number of vehicles that can travel along a route. However, in more practical situations, it is considered as a sufficiently large number.

A vehicle can be reused, i.e., perform total multiple trips over the time horizon. Based on the 2011 floods and landslides in the Serrana region of Rio de Janeiro State in Brazil, Figure 1 shows an example where vehicles must complete 3 trips from a depot in Nova Friburgo (NFR) to relief centers located in Santa Maria Madalena (SMM), Petrópolis (PTP), and Sapucacia (SPC) over a time horizon of 2 periods of 6 hours each. Figure 2 shows two contrasting schedules for the 3 trips: when resources are sufficient (3 vehicles available) and when resources are scarce (1 vehicle available). When no multiple trips are permitted, then 3 vehicles are needed as each route requires a vehicle. When partial multiple trips over the time horizon are permitted, but not within each time period (case i), then vehicles can be (re)used only at the beginning of the next time period, so vehicle 2 is needed to perform trip 3. When partial multiple trips within each time period are permitted (case ii), vehicle 1 is free at the end of period 1 and so can be reused for trip 2. However, trips 2 or 3 cannot occur in period 1 because the total travel time is greater than the period's length. Finally, when total multiple trips are permitted (case i+ii), a single available vehicle can perform all the trips, saving resources. Within the traditional approaches, if only one vehicle is available, then at least one trip cannot happen, causing an unnecessary shortage of commodities.

There are relief inventory at depots and RCs. The first case refers to the total quantity of in-kind donations not sent to the RCs yet, thus remaining at the depots from one period to another at least. Those commodities that were already sent to the RCs in a given period, but not used to prompt satisfy victims needs of the same period, compose the RCs inventory. We assume that the relief inventory at the depots are not affected by the disaster because those facilities are always located in safe places. However, relief inventory can be damaged at the RCs depending on the disaster impact and effects, analogously to Galindo and Batta (2013), among others, in which it is considered the potential destruction of supplies that were stored near the demand points. We penalize only the relief inventory at the RCs to avoid keeping a great amount of unused goods in those facilities, which might disrupt the humanitarian assistance there.

We assume that either victims travel from the affected areas to the RCs seeking emergency commodities or they were already evacuated from the affected areas to the RCs by relief agencies. In both cases, there is a cost to be paid by either agencies or victims, which it is defined here as

Figure 1: Illustrative example with 3 trips.

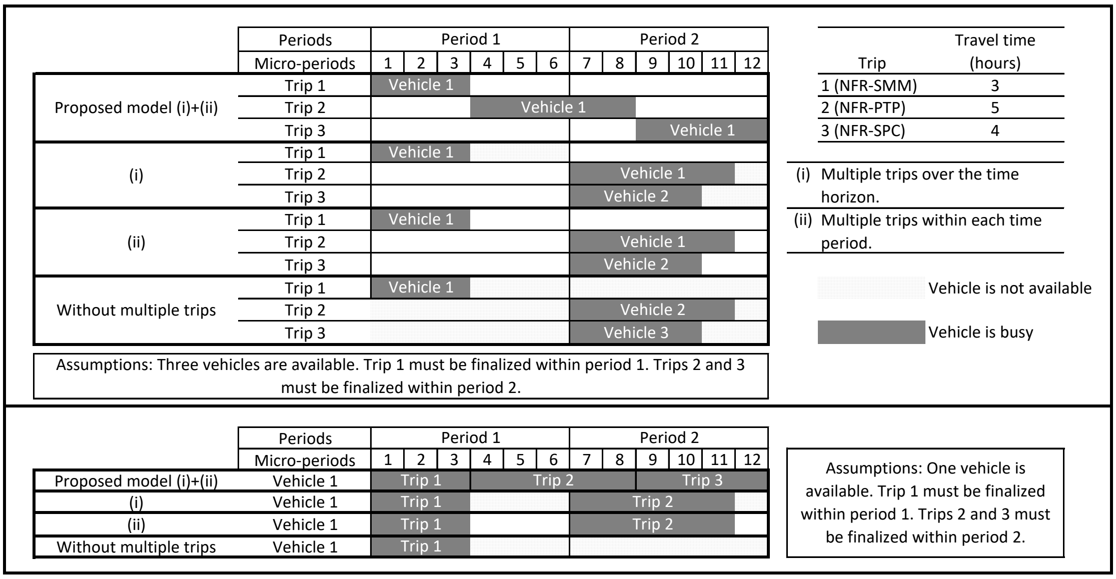

Figure 2: Schedule with multiple trips.

"the cost of meeting victims' needs". Clearly, this cost involves transportation and it is supposed to increase for longer distances. For this reason, it makes sense to assume that is proportional to the distance between RCs and affected areas. Such costs are deemed zero if a relief center is in the same geographical region as the affected area. This assumption stimulates the pre-selection of RCs that are closer to affected areas.

Since the incoming supply is random, it can arise in a smaller quantity than required by the victims, causing unfulfilled needs. In order to take into account human suffering as a consequence of the relief aid shortage, we propose to use the idea of deprivation costs to *prioritize* demand fulfillment to those people who are deprived from a given relief aid for longer. The next section presents our two-stage stochastic multi-trip location-transportation model with social concerns, denoted model FLTP.

3.1. Indexes and Sets

$w \in W$	Emergency commodities.
$i \in I$	Depots.
$j \in J$	Relief centers.
$k \in K$	Affected Areas.
$l \in L$	Types of Vehicles.
$\xi \in \Xi$	Scenarios.
$t \in T$	Time periods.
$\theta \in \Theta$	Micro-periods.
$\Theta(t) \subseteq \Theta$	Subset of the micro-periods within period t.
$\theta_t^F \subseteq \Theta(t)$	First micro-period of period t.
$\theta_t^L \subseteq \Theta(t)$	Last micro-period of period t.
$\delta \in \Delta_w$	Deprivation time for commodity w in terms of micro-periods.

The relationship between periods and micro-periods is illustrated in Figure 3. For example, with a time horizon of 4 day-long periods and micro-periods of 4 hours, $\{\theta_1^F, \theta_2^F, \theta_3^F, \theta_4^F\} = \{1, 7, 13, 19\}$ and $\{\theta_1^L, \theta_2^L, \theta_3^L, \theta_4^L\} = \{6, 12, 18, 24\}$. If demand for commodity 1 can remain unmet for up to 6 micro-periods, then the corresponding deprivation set is posed as $\Delta_1 = \{1, 2, 3, 4, 5, 6\}$. Note that θ is the index regarding micro-periods, whereas δ is the index associated with the amount of time "in deprivation" which is evaluated in the number of micro-periods.

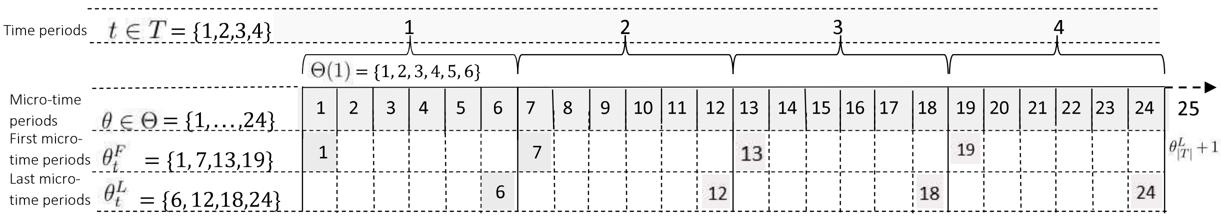

Figure 3: A time horizon of 4 day-long periods and micro-periods of 4 hours.

3.2. Deterministic Parameters

α_j	Fixed cost for opening and operating relief center j.
β_l (β_l')	Fixed cost of vehicle type l in the first-stage (second-stage).
γ_{ijl}	Shipping cost for vehicle type l in the predetermined route (i, j).
κ_w	Inventory cost of commodity w.
η_{kj}	Cost of relief center j serving affected area k.
ν_w (ν_w')	Volume (weight) of commodity w.
ϑ_l (ϑ_l')	Capacity by volume (weight) of vehicle type l.
ρ_j (ρ_{wj}')	Capacity of relief center j by volume (number of commodity type w).
φ_{ijl}	Maximum number of vehicles type l that can travel along arc (i, j) at each micro-period.
ϕ_l	Maximum number of vehicles type l available in the first-stage.
$g_w(\delta)$	Deprivation cost of commodity w as a function of the deprivation time $\delta \in \Delta_w$.
$\lvert\Delta_w\rvert$	Number of micro-periods from which unmet demand reaches the maximum penalty.
$g_w(\lvert\Delta_w\rvert)$	Maximum deprivation cost of commodity w.
τ_{ijl}	Travel time of vehicle l along arc (i, j).

3.3. Stochastic parameters

q^{ξ}_{wit} Incoming supply of commodity w at depot i in period t in scenario ξ.
p^{ξ}_{wjt} Proportion of commodity w at relief center j in period t which remains usable in scenario ξ.
d^{ξ}_{wkt} Demand for commodity w in affected area k in period t in scenario ξ.
a^{ξ}_{ijlt} $= 1$, if route (i, j) is available for vehicle type l in period t in scenario ξ.
$= 0$, otherwise.
π^{ξ} Probability of occurrence of scenario ξ.

3.4. First-stage decision variables

N_{li} Quantity of vehicles type l procured in the first-stage at depot i.
Y_j $= 1$, if relief center j is open.
$= 0$, otherwise.

3.5. Second-stage decision variables

N'_{lit} Quantity of vehicles type l procured in the second-stage at depot i at period t in scenario ξ.
$P^{\theta\xi}_{wijl}$ Amount of commodity w shipped from depot i to relief center j using vehicle l at micro-period $\theta \in \Theta$ in scenario ξ.
$V^{\theta\xi}_{ijl}$ Number of vehicles type l that start the distribution along route (i, j) at micro-period $\theta \in \Theta$ in scenario ξ.
$Z^{\theta\xi}_{wjkt}$ Delivery quantity of commodity w in relief center j at micro-period $\theta \in \Theta$ to supply the need of affected area k in period t in scenario ξ.
ID^{ξ}_{wit} Inventory of commodity w in depot i at period t in scenario ξ.
IRC^{ξ}_{wjt} Inventory of commodity w in relief center j at period t in scenario ξ.
$U^{\theta\xi}_{wkt}$ Demand of commodity w from affected area k in period t that remains unmet until micro-period $\theta \in \{\Theta \cup \{\theta^L_{|T|} + 1\}\}$ in scenario ξ.
$TU^{\xi}_{w}(\delta)$ Total demand of commodity w that remains unmet for δ deprivation micro-periods in scenario ξ.

3.6. Objective Function

The objective function of the model FLTP is formulated as follows:

$$\min \quad \{f^{LC}, f^{DC}\} \tag{1}$$

where

$$\begin{aligned} f^{LC} = \quad & \sum_{j\in J} \alpha_j \cdot Y_j + \sum_{i\in I}\sum_{l\in L}\left(\beta_l \cdot N_{li} + \sum_{t\in T}\sum_{\xi\in\Xi} \pi^{\xi} \cdot \beta'_l \cdot N'^{\xi}_{lit}\right) + \\ & \sum_{j\in J}\sum_{\theta\in\Theta}\sum_{\xi\in\Xi} \pi^{\xi} \cdot \left(\sum_{i\in I}\sum_{l\in L} \gamma_{ijl} \cdot V^{\theta\xi}_{ijl} + \sum_{k\in K}\sum_{t\in T}\sum_{w\in W} \eta_{kj} \cdot Z^{\theta\xi}_{wjkt}\right) + \\ & \sum_{j\in J}\sum_{t\in T}\sum_{w\in W}\sum_{\xi\in\Xi} \pi^{\xi} \cdot \kappa_w \cdot IRC^{\xi}_{wjt}, \end{aligned} \tag{2}$$

and

$$\begin{aligned} f^{DC} = \sum_{w\in W}\sum_{\xi\in\Xi} \pi^{\xi} \cdot \Bigg[& \sum_{\delta\in\Delta_w} (g_w(\delta) - g_w(\delta - 1)) \cdot TU^{\xi}_{w}(\delta) + \\ & \sum_{k\in K}\sum_{t\in T} \max\{g_w(|\Delta_w|) - g_w(|\Theta| - \theta^L_t + 1), 0\} \cdot U^{(\theta^L_{|T|}+1)\xi}_{wkt} \Bigg]. \end{aligned} \tag{3}$$

The objective function (1) minimizes both expected logistics costs (2) and human suffering (3). Function (2) involves the first-stage costs of opening or operating relief centers and acquiring vehicles before a disaster, respectively, and the second-stage costs of acquiring vehicles after a disaster, shipping emergency commodities, supplying the affected areas, and holding inventory at relief center nodes, respectively. Function (3) is the monetary cost of depriving victims of emergency commodities over a number of micro-periods. We use two ways to account for both objectives: (i) via a bi-objective model that prioritizes f^{DC} over f^{LC} (Section 4.1) and (ii) merging both functions into a single objective, i.e., $f^{LC} + f^{DC}$.

The demand of a period t can be satisfied in any micro-period of the period t without be considered as unmet demand. If the demand of period t is not promptly satisfied in period t it is considered unmet from the first micro-period of period $t+1$ ($\theta_t^L + 1$, or equivalently, θ_{t+1}^F) with one micro-period of deprivation and can be satisfied in some of the next periods $t'(t' > t)$ incurring in deprivation costs or can be lost if it is not satisfied within the maximum deprivation time $|\Delta_w|$ incurring in the maximum deprivation cost $g_w(|\Delta_w|)$. For example, with a time horizon of 4 days and 6 micro-periods of 4 hours each every day, as shown in Figure 3, the demand of period $t = 1$ is considered unmet from micro-period 7 onwards since $\theta_1^L + 1 = \theta_2^F = 7$. Following this rationale, the demand of the last period $|T|$ is counted as unmet in the "dummy" micro-period $\theta_{|T|}^L + 1 = \theta_4^L + 1 = 25$. Here, we use the general term "unmet demand" in two situations: Firstly, a *shortage* when a given demand is not satisfied in the current period, but is backlogged to be satisfied later. Secondly, a *lost demand* when a given demand is not satisfied during the entire time horizon.

Following this reasoning, the first term of equation (3) penalizes the shortage of commodities while the second term penalizes the lost demand in the final "dummy" micro-period $\theta_{|T|}^L + 1$. Demands that remain unmet over a deprivation time of δ micro-periods have also not been satisfied for deprivation times of $\delta - 1, \delta - 2, ..., 1$ micro-periods. So, to avoid double-counting, the first term of the objective function (3) does not consider the cost $g_w(\delta)$, but rather $g_w(\delta) - g_w(\delta - 1)$. For example, let $\Delta_w = \{1, 2, 3\}$ and assume that a given demand is unmet for $\delta = 3$ micro-periods. Then the resulting deprivation cost is $[g_w(3) - g_w(2)] + [g_w(2) - g_w(1)] + [g_w(1) - g_w(0)] = g_w(3)$, with $g_w(0) = 0$. If the cost $g_w(\delta)$ were used, then the resulting deprivation cost would be $g_w(3) + g_w(2) + g_w(1)$ which overestimates the actual cost.

A demand d_{wkt}^{ξ} that is not fulfilled in any micro-period $\theta \in \Theta$ during the time horizon is considered lost and must be penalized with the maximum deprivation cost $g_w(|\Delta_w|)$. In this case, the deprivation cost is evaluated in the dummy micro-period $\theta_{|T|}^L + 1$. For example, let $\Delta_w = \{1, 2, 3, 4, 5\}$ in a time horizon of 4 days and 6 micro-periods every day, as shown Figure 3. Thus lost demand must be penalized with $g_w(5)$. According to our modeling assumptions, any unmet demand in the last period $t = 4$ arises in micro-period $\theta_{|T|}^L = 24$ and becomes unmet in micro-period $\theta_{|T|}^L + 1 = 25$, with a total deprivation time of one micro-period as a result of the difference between $\theta_{|T|}^L + 1$ and $\theta_{|T|}^L$. Notice that, as the planning horizon ends at the dummy micro-period 25, the unmet demand of period 4 will never reach more than one micro-period of deprivation. So it suffices to penalize this unmet demand in the first term of equation (3) with $g_w(1) - g_w(0) = g_w(1)$, where $g_w(0) = 0$. However, as this unmet demand was not met in the time horizon, it must be penalized with $g_w(5)$ according to our modeling assumptions. So we need to add an extra penalization of $\max\{g_w(|\Delta_w|) - g_w(|\Theta| - \theta_4^L + 1), 0\} = \max\{g_w(5) - g_w(24 - 24 + 1), 0\} = \max\{g_w(5) - g_w(1), 0\} = g_w(5) - g_w(1)$ in the second term of equation (3) to obtain the total penalty value $g_w(5)$. We must subtract $g_w(1)$ from the second term of equation (3) because this term was already counted in the first term of equation (3), otherwise the penalization would be $g_w(5) + g_w(1)$ and not $g_w(5)$. Note that without the second term ($\max\{g_w(|\Delta_w|) - g_w(|\Theta| - \theta_4^L + 1), 0\}$), the last period's unmet demand would be penalized using just $g_w(1)$, which represents the lowest deprivation cost. Note also that the demand of period $t = 3$ is considered unmet from micro-period $\theta = 19$, with a deprivation cost of $g_w(1)$, to micro-period $\theta = 23$, with a total deprivation cost of $g_w(5)$

i.e., $\max\{g_w(5) - g_w(24-18+1), 0\} = \max\{g_w(5) - g_w(7), 0\} = 0$. In this case, because $g_w(\delta) \geq g_w(\delta')$, $\forall \delta \geq \delta'$, there is no need to include the deprivation cost at the end of the time horizon. Although $g_w(\delta)$ is a non-linear function, it is a parameter and so the model remains linear.

3.7. Constraints

Flow conservation. Constraints (4) and (5) conserve the flow of commodities at depots and relief centers, respectively. We assume that depots are located only in non-vulnerable areas, but relief centers can be located in vulnerable (disaster) areas as well. Thus inventory that can be carried forward from one period to the next is reduced by the proportion of usable inventories p^{ξ}_{wjt} in (5). Thus, the proportion of usable inventories p^{ξ}_{wjt} considers that some products can become obsolete during the disaster. Parameter $p^{\xi}_{wjt} = 1$, for example, indicates that there is no obsolete inventory. On the other hand, $p^{\xi}_{wjt} = 0.05$ indicates that only 5% of the product w is kept in inventory at relief center j from period $t-1$ to period t. As the parameter p^{ξ}_{wjt} is an index in t, it can control the obsolescence of the inventory in each time period.

$$q^{\xi}_{wit} + ID^{\xi}_{wi(t-1)} = \sum_{j\in J}\sum_{l\in L}\sum_{\theta\in\Theta(t)} P^{\theta\xi}_{wijl} + ID^{\xi}_{wit},\ \forall w \in W,\ i \in I,\ t \in T,\ \xi \in \Xi \tag{4}$$

$$\sum_{i\in I}\sum_{l\in L}\sum_{\theta\in\Theta(t)} P^{(\theta-\tau_{ijl})\xi}_{wijl} + p^{\xi}_{wjt} \cdot IRC^{\xi}_{wj(t-1)} = \sum_{k\in K}\sum_{\theta\in\Theta(t)}\sum_{t'=1}^{t} Z^{\theta\xi}_{wjkt'} + IRC^{\xi}_{wjt}, \tag{5}$$
$$\forall w \in W,\ j \in J,\ t \in T,\ \xi \in \Xi.$$

Constraints (6) keep the supply of commodities to affected areas within their availability. Note that commodities are available in relief centers τ_{ijl} micro-periods after leaving depots. For example, if $\tau_{ijl} = 2$, then commodity w shipped in vehicle type l from depot i in micro-period $\theta = 5$ is available in relief center j from micro-period 7 onwards. Both constraints (5) and (6) allow available commodities in relief centers to fulfill demand in a period ($t' = t$) or unmet demand from past periods ($t' = 1$ to $t' = t-1$).

$$\sum_{k\in K}\sum_{\theta'=\theta^F_t}^{\theta}\sum_{t'=1}^{t} Z^{\theta'\xi}_{wjkt'} \leq p^{\xi}_{wjt} \cdot IRC^{\xi}_{wj(t-1)} + \sum_{i\in I}\sum_{l\in L}\sum_{\theta'=\theta^F_t}^{\theta} P^{(\theta'-\tau_{ijl})\xi}_{wijl} \tag{6}$$
$$\forall\ w \in W, j \in J, \theta \in \Theta(t), t \in T, \xi \in \Xi.$$

Capacity of relief centers. Constraints (7) and (8) limit transportation to be only from depots to existing relief centers. Based on practical disaster operations, the flow of emergency commodities arriving in relief centers respects a total capacity in volume (ρ_j) and a per type of product (ρ'_{wj}) capacity. The per-product capacity reflects that some relief centers may not be able to store certain commodities, e.g., vaccines that need refrigeration.

$$\sum_{w\in W}\sum_{i\in I}\sum_{l\in L}\sum_{\theta\in\Theta(t)} \nu_w \cdot P^{(\theta-\tau_{ijl})\xi}_{wijl} + \sum_{w\in W} \nu_w \cdot IRC^{\xi}_{wj(t-1)} \leq \rho_j \cdot Y_j,\ \forall j \in J,\ t \in T,\ \xi \in \Xi. \tag{7}$$

$$\sum_{i\in I}\sum_{l\in L}\sum_{\theta\in\Theta(t)} P^{(\theta-\tau_{ijl})\xi}_{wijl} + IRC^{\xi}_{wj(t-1)} \leq \rho'_{wj} \cdot Y_j,\ \forall w \in W,\ j \in J,\ t \in T,\ \xi \in \Xi. \tag{8}$$

Capacity of vehicles. Constraints (9) and (10) state that each vehicle has certain capacity in terms of volume (ϑ_l) and weight (ϑ'_l) and the products must comply with it.

$$\vartheta_l \cdot V^{\theta\xi}_{ijl} \geq \sum_{w\in W} \nu_w \cdot P^{\theta\xi}_{wijl},\ \forall i \in I,\ j \in J,\ l \in L,\ \theta \in \Theta,\ \xi \in \Xi. \tag{9}$$

$$\vartheta'_l \cdot V^{\theta\xi}_{ijl} \geq \sum_{w\in W} \nu'_w \cdot P^{\theta\xi}_{wijl},\ \forall i \in I,\ j \in J,\ l \in L,\ \theta \in \Theta,\ \xi \in \Xi. \tag{10}$$

Procurement of vehicles in both stages. Constraints (11) limit the number of each type of vehicle that can be procured in the first-stage. There are no limits in the second-stage. Constraints (12) ensure that only vehicles that were assigned to depots in either the first or second-stage may be used to transport supplies to relief centers. These constraints also reflect that each vehicle can make multiple round trips (depot $i \rightarrow$ relief center $j \rightarrow$depot i) during the whole time horizon. Since travel times on routes (i, j) and (j, i) are equal, each vehicle takes $2 \cdot \tau_{ijl}$ micro-periods for a single round trip. For example, if $\tau_{ijl} = 2$ and vehicle type l arrives at relief center j from depot i in micro-period $\theta = 8$, then this vehicle is busy in micro-periods 5, 6, 7, and 8 because the round trip takes $2 \cdot \tau_{ijl} = 4$ micro-periods, i.e., from micro-period $\theta - (2 \cdot \tau_{ijl} - 1) = 5$ to micro-period $\theta = 8$.

$$\sum_{i \in I} N_{li} \leq \phi_l, \ \forall \ l \in L \tag{11}$$

$$\sum_{j \in J} \sum_{\theta' = \theta - (2 \cdot \tau_{ijl} - 1)}^{\theta} V_{ijl}^{\theta' \xi} \leq N_{li} + N'^{\xi}_{lit}, \ \forall \ i \in I, \ l \in L, \ \theta \in \Theta(t), \ t \in T, \ \xi \in \Xi. \tag{12}$$

Note how general constraints (12) are. For example, if there is a setup time to use a vehicle again, then it suffices to include it in the vehicle's travel time. In example of Figure 2, even with a setup time of 5 micro-periods (5 hours), it would still be possible to use the same vehicle to perform trip 2. If the setup time was 4 micro-periods (4 hours), then the vehicle can perform trip 3.

Availability of arcs. Constraints (13) prevent a vehicle of type l travelling on an arc (i, j) in any micro-period θ of a period t in scenario ξ if the arc is not available in that period for this type of vehicle. For example, floods and landslides may cause the collapse of arc (i, j) for land transportation, but not for air transport. Note that if arc (i, j) is available ($a^{\xi}_{ijlt} = 1$), then constraints (13) provide an upper bound for the total number of vehicles that can travel along the arc, which is usually a large number. It is also possible to consider a reduced φ_{ijl} to represent some situations where the arcs are partially damaged, so there will be a limited number of vehicles that can traverse them.

$$\sum_{\theta' = \theta - (2\tau_{ijl} - 1)}^{\theta} V_{ijl}^{\theta' \xi} \leq \varphi_{ijl} \cdot a^{\xi}_{ijlt}, \ \forall i \in I, \ j \in J, \ l \in L, \ \theta \in \Theta(t), \ t \in T, \ \xi \in \Xi. \tag{13}$$

Evaluation of unmet demand. Constraints (14) evaluate the unmet demand of period t in the first micro-period of period $t+1$, i.e., in micro-period $\theta^L_t + 1$. Note that the unmet demand in a period t is equal to the demand of period t (d^{ξ}_{wkt}) minus the quantity of commodities delivered ($\sum_{j \in J} \sum_{\theta \in \Theta(t)} Z^{\theta \xi}_{wjkt}$) for the demand of period t. For instance, Figure 4 shows the unmet demand of periods 1 and 2, calculated in micro-periods 7 and 13, as $d^{\xi}_{wk1} - Z^{1\xi}_{wjk1} - Z^{4\xi}_{wjk1} = 10 - 2 - 4 = 4$ and $d^{\xi}_{wk2} - Z^{8\xi}_{wjk2} - Z^{12\xi}_{wjk2} = 5 - 2 - 2 = 1$, respectively. Thus, constraints (14) define the initial unmet demand of each period. On the other hand, constraints (15) define the demand that remains unsatisfied in the next micro-periods until reaching the maximum deprivation time $|\Delta_w|$, i.e., from micro-period $\theta^L_t + 2$ to micro-period $\theta^L_t + |\Delta_w|$. If $\Delta_w = \{1, 2, 3\}$, for example, we need to calculate the unmet demand of period 1 until the micro-period $\theta^L_1 + 3 = 9$. Figure 4 shows the demand of period 1 that remains unmet for micro-periods 8 and 9 calculated as $U^{8\xi}_{wk1} = U^{7\xi}_{wk1} - Z^{7\xi}_{wjk1} = 4 - 1 = 3$ and $U^{9\xi}_{wk1} = U^{8\xi}_{wk1} - Z^{8\xi}_{wjk1} = 3 - 3 = 0$, respectively. Finally, constraints (16) define the total amount of demand for each commodity and scenario that remains unsatisfied for δ micro-periods, based on the unmet demand calculated in constraints (14) and (15). The unmet demand of period 1 of Figure 4, for example, remains unmet for $\delta = 2$ micro-periods of deprivation if it was not fulfilled until the micro-period $\theta^L_1 + 2 = 6 + 2 = 8$, while the demand of period 2 remains unmet for $\delta = 2$ micro-periods if it was not fulfilled until the micro-period $\theta_1^L + 2 = 12 + 2 = 14$. Then, $TU_w^\xi(2) = U_{wk1}^{8\xi} + U_{wk2}^{14\xi} = 3 + 2 = 5$.

$$U_{wkt}^{(\theta_t^L+1)\xi} = d_{wkt}^\xi - \sum_{j\in J}\sum_{\theta\in\Theta(t)} Z_{wjkt}^{\theta\xi}\ , \quad \forall\, w\in W, k\in K, t\in T, \xi\in\Xi. \tag{14}$$

$$U_{wkt}^{\theta\xi} = U_{wkt}^{(\theta-1)\xi} - \sum_{j\in J} Z_{wjkt}^{(\theta-1)\xi}\ ,$$

$$\forall\, w\in W, k\in K, t\in T, \xi\in\Xi, \theta\in \left\{\Theta\cup\{\theta_{|T|}^L+1\} : \theta_t^L+2 \le \theta \le \theta_t^L + |\Delta_w|\right\}. \tag{15}$$

$$TU_w^\xi(\delta) = \sum_{t\in T}\sum_{k\in K} U_{wkt}^{(\theta_t^L+\delta)\xi}\ , \quad \forall\, w\in W, \delta\in\Delta_w, \xi\in\Xi. \tag{16}$$

d_{wkt}^ξ	10						5						9						
$Z_{wjk1}^{\theta\xi}$	2			4			1	3											
$Z_{wjk2}^{\theta\xi}$								2				2		2					
$Z_{wjk3}^{\theta\xi}$													3	5					
$U_{wkt}^{\theta\xi}$							4	3	0				2	2	0				1
Micro-periods	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Periods	1						2						3						

Figure 4: Example of unmet demand in a time horizon divided in 3 days and each day divided into 6 micro-periods of 4 hours each.

Domain of the decision variables. Constraints (17), (18) and (19) define the domains of the decision variables.

$$Y_j \in \mathbb{B},\ \forall j\in J. \tag{17}$$

$$V_{ijl}^{\theta\xi} \in \mathbb{Z}^+,\ \forall i\in I,\ j\in J,\ l\in L,\ \theta\in\Theta,\ \xi\in\Xi. \tag{18}$$

$$N_{li},\ N_{lit}^{\prime\xi},\ P_{wijl}^{\theta\xi}, Z_{wjkt}^{\theta\xi},\ IRC_{wjt}^\xi,\ ID_{wit}^\xi,\ U_{wkt}^{\theta\xi},\ TU_w^\xi(\delta)\in\mathbb{R}^+, \tag{19}$$

$$\forall\, i\in I,\ j\in J,\ l\in L,\ w\in W,\ t\in T,\ \theta\in\Theta,\ \delta\in\Delta,\ \xi\in\Xi.$$

4. Solution approaches

4.1. Solving the bi-objective problem

There are various techniques to solve multi-objective optimization models, such as hierarchical optimization (Anandalingam and Friesz, 1992), goal programming (Romero, 1991), and the epsilon constraint method (Haimes et al., 1971). In this paper, we use a bi-level hierarchical optimization procedure. At the first level, model FLTP is solved via the minimization of the deprivation costs (f^{DC}), then the minimum deprivation cost (f^{DC*}) is added as a constraint ($f^{DC} \le f^{DC*}$) and the model re-solved at the second level minimizing overall logistics costs (f^{LC}). Note that the new constraint added at the second level is always feasible unless the first level optimization problem is already infeasible. This hierarchical procedure reflects humanitarian principles where saving lives as fast as possible − via the minimization of the deprivation cost − is paramount and the efficient use of scarce resources via the minimization of the logistics costs takes secondary importance.

This approach is also flexible enough to include a *deviation variable*, say *dev* (such that $f^{DC} \le f^{DC*} + dev$) is minimized in the objective function at the second level of the procedure. This analysis can be useful when there is a clear justification for trading off shortages of emergency commodities with lower logistics costs.

4.2. Solving the MIP problems

Both levels require solving a relatively complex MIP problem even for small instances. For example, an instance with 3 depots, 8 relief centers, 5 affected areas, 3 commodities, 10 time periods, 240 micro-periods (of one hour each), 3 scenarios, 2 vehicles, and a maximum deprivation time of 96 micro-periods implies a problem with more than 909,526 variables (51,840 of which are integer) and 25,784 constraints. Even though this problem size is not necessarily prohibitive for commercial solvers such CPLEX, the numerical tests below show that the second-level problem cannot be efficiently solved without exploiting specialized solution methods.

By recognizing that our model FLTP is a combination of different structural elements, such as multiple periods and micro-periods, commodities, nodes (depots and relief centers), vehicles, and scenarios, we develop three heuristics based on decomposition and mathematical programming techniques to provide good-quality solutions within a plausible amount of time: a fix-and-optimize heuristic (FXO), a two-step heuristic based on an approximate model (TSH), and a hybrid heuristic that combines FXO and TSH.

4.2.1. Fix-and-Optimize heuristic (FXO)

In a traditional fix-and-optimize (FXO) heuristic, a given initial solution is improved iteratively. A partition criterion is specified whereby the variables of each partition are iteratively fixed and/or unfixed in an attempt to produce smaller and easier MIPs. Each MIP consists of integer variables specific to the current iteration (partition) that must be optimized and integer decisions that are fixed according to the incumbent solution. If the resulting solution is better than the incumbment solution, then the incumbent is updated. The process is repeated until reaching a given stopping criteria, e.g., after a time limit, or after a number of iterations without improvement in the solution.

The initial solution here is generated by not satisfying any demand, i.e., all the decision variables are set to zero, with exception of those for unmet demand. As in Moreno et al. (2016), time horizon decomposition is used to fix/unfix the discrete variables $V_{ijl}^{\theta\xi}$. Assume that $\mathbf{V}^{\theta} = [V_{ijl}^{\theta\xi}, \forall(i,j,l,\xi)]$. Then, at each iteration, the algorithm maintains the integrality of variables $\mathbf{V}^{\theta}$, where $\theta \in \Theta(t)$ refers to the micro-periods in the current time period t. Simultaneously, all the remaining variables, i.e., $\mathbf{V}^{\theta} : \theta \in \Theta(t)$, where t is not the current period, are fixed according to the incumbent solution. A pseudo code for this FXO algorithm is outlined in Algorithm 1.

Algorithm 1 FXO heuristic.

```
Initialization: Generate an initial solution. Fix all variables at their current values. Define a
    partition 𝒫_t for the discrete variables V_ijl^{θξ} : θ ∈ Θ(t).
Incumbent solution := initial solution; OF_incumbent := objective function of the initial solution.
LastImprovement:=0; t' := |T|.
while iter¡IterLimit do
    for t = |T| to 1 do
        if t = t' and LastImprovement=1 then
            Stop.
        else
            Unfix variables from set P_t.
            Solve the resulting subproblem.
            if OF_MIP ¡ OF_incumbent then
                LastImprovement := 0; t' := t.
                Incumbent solution := MIP solution
                OF_incumbent:= OF_MIP
            end if
            Fix all variables according to the incumbent solution.
        end if
    end for
    LastImprovement:=1;
end while
```

Note. *OF_MIP*: objective function of the subproblem. *OF_incumbent*: objective function of the incumbent solution. LastImprovement: controls if there is an improvement in the objective function of the incumbent solution. IterLimit: maximum number of iterations.

4.2.2. Two-step heuristic (TSH)

In the first step of the two-step heuristic, an approximate linear programming version of the original mathematical model is solved in order to obtain location and transportation decisions. In the second step, the original formulation is solved with the information gathered from the approximate model and the fleet sizing decisions thus determined. Algorithm 2 shows the two-step heuristic.

Algorithm 2 Two-step heuristic.

1. **Step 1:** Solve the approximate location-transportation model (ALTP). The objective f^{DC} is solved at the first level and the objective f^{ALC} at the second level.
2. Fix variables $P_{wijl}^{\theta\xi}$, $Z_{wjkt}^{\theta\xi}$, IRC_{wjt}^{ξ}, ID_{wit}^{ξ}, $U_{wkt}^{\theta\xi}$, and $TU_{w}^{\xi}(\delta)$ at their values obtained in step 1.
3. **Step 2:** Solve the original FLTP model (1)−(19) via the minimization of f^{LC}.

Model ALTP is posed as follows:

$$\min \{f^{ALC}, f^{DC}\} \tag{20}$$

$$\text{s.t.: constraints } (4) - (8), (14) - (19)$$

$$\sum_{\theta'=\theta-(2\tau_{ijl}-1)}^{\theta} \frac{\sum_{w\in W} b_w \cdot P_{wijl}^{\theta'\xi}}{\vartheta_l} \leq (\varphi_{ijl} - 2\tau_{ijl}) \cdot a_{ijlt}^{\xi},$$

$$\forall i \in I,\ j \in J,\ l \in L,\ \theta \in \Theta(t),\ t \in T,\ \xi \in \Xi. \tag{21}$$

$$\sum_{\theta'=\theta-(2\tau_{ijl}-1)}^{\theta} \frac{\sum_{w\in W} b'_w \cdot P_{wijl}^{\theta'\xi}}{\vartheta'_l} \leq (\varphi_{ijl} - 2\tau_{ijl}) \cdot a_{ijlt}^{\xi},$$

$$\forall i \in I,\ j \in J,\ l \in L,\ \theta \in \Theta(t),\ t \in T,\ \xi \in \Xi. \tag{22}$$

$$Y_j,\ P_{wijl}^{\theta\xi}, Z_{wjkt}^{\theta\xi},\ IRC_{wjt}^{\xi},\ ID_{wit}^{\xi},\ U_{wkt}^{\theta\xi},\ TU_w^{\xi}(\delta) \in \mathbb{R}^+, \tag{23}$$

$$\forall\ i \in I,\ j \in J,\ l \in L,\ w \in W,\ t \in T,\ \theta \in \Theta,\ \delta \in \Delta,\ \xi \in \Xi.$$

in which

$$f^{ALC} = \sum_{j\in J} \alpha_j \cdot Y_j + \sum_{w\in W}\sum_{j\in J}\sum_{t\in T}\sum_{\xi\in\Xi} \pi^{\xi} \cdot \left(\kappa_w \cdot IRC^{\xi}_{wjt} + \sum_{k\in K}\sum_{\theta\in\Theta} \eta_{kj} \cdot Z^{\theta\xi}_{wjkt} \right) + \tag{24}$$
$$\sum_{w\in W}\sum_{i\in I}\sum_{j\in J}\sum_{l\in L}\sum_{\theta\in\Theta}\sum_{\xi\in\Xi} \pi^{\xi} \cdot \left(\frac{\beta_l}{|T|} + \beta'_l + \gamma_{ijl} \right) \cdot \quad \frac{\nu_w}{2\vartheta_l} + \frac{b'_w}{2\vartheta'_l} \Bigg) \cdot P^{\theta\xi}_{wijl}.$$

The objective (24) differs from (2) regarding the evaluation of shipping and fixed costs of contracting vehicles. Model ALTP determines shipping and fixed costs using the relation $\left(\frac{\nu_w}{2\vartheta_l} + \frac{\nu'_w}{2\vartheta'_l}\right) \cdot P^{\theta\xi}_{wijl}$, which is an approximation of the number of vehicles used by micro-period in the second-stage. Note that the objective function (24) underestimates the total shipping cost and overestimates the fixed cost of vehicles.

The model ALTP does not consider the variables related to the fleet sizing decisions, i.e., $V^{\theta\xi}_{ijl}$, N_{li}, N'^{ξ}_{lit}, and the binary variable associated with the relief centers Y_j. Thus constraints (9)−(13) are dropped and the new approximate constraints (21) and (22) are added to ensure that the original model FLTP solved in the second step will produce a feasible solution regarding the minimum number of vehicles needed to transport aid. The arc capacity φ_{ijl} is reduced by a factor $2\tau_{ijl}$ in order to avoid infeasibility when the approximate number of vehicles $(\frac{\nu_w}{\vartheta_l} + \frac{\nu'_w}{\vartheta'_l}) \cdot P^{\theta\xi}_{wijl}$ are rounded up and used in the second step of the heuristic to evaluate the (integer) number of vehicles $V^{\theta\xi}_{ijl}$ for each scenario. Constraints (23) define the domain of the decision variables.

4.2.3. Hybrid heuristic (TSH+FXO)

The third heuristic (TSH+FXO) is a hybrid strategy based on the previous two heuristics, whereby the solution of the TSH heuristic is used as the initial solution of the FXO heuristic.

5. Computational results

The main goal of this section is twofold: firstly, to analyze the performance of the proposed solution approaches for the model FLTP; secondly, to analyze the performance of the model regarding the impact of the total multiple trips and deprivation costs, being the main novel characteristics of our model. All models and methods were coded in GAMS 24.1.3 and optimized via the solver CPLEX 12.5 on an Intel Xeon E5-1650 processor with 32 GB RAM under the Windows 7 operating system. The stopping criteria to solve the hierarchical bi-level model were either elapsed times exceeding 3,600 seconds or optimality gaps relative to the best lower bound becoming smaller than 0.1%. Following a hierarchical approach, the optimization model of the second level was solved only if the optimality gap of the first level is approximately zero.

This section is organized as follows. Subsection 5.1 presents the scenario generation. Subsection 5.2 describes the data instances. Subsection 5.3 presents how deprivation costs were estimated. Subsection 5.4 analyzes the performance of the solution approaches for a set of practical instances. Subsection 5.5 discusses the performance of the model focusing on its novel characteristics. Finally, Section 5.6 shows the impact of the randomness via the evaluation of both Expected Value of Perfect Information and Value of Stochastic Solution.

5.1. Scenario generation

The scenario generation was based on the method developed in Moreno et al. (2016), which estimates the stochastic data according to the type/magnitude of previous disasters in the same geographical region. This method comprises four main parts: 1) analysis of historical data; (2) disaster categorization; (3) bootstrap phase; and (4) scenarios evaluation.

1. Analysis of historical data. Firstly, we carried out a careful research on the number of floods and landslides in the State of Rio de Janeiro from 1966 to 2013, as well as their corresponding number of affected people. These data were directly obtained from EM-DAT (2015). This investigation generated columns 2 and 3 of Table 2.

2. Disaster categorization. The disasters were classified as either emergency situation, crisis situation, minor disaster, moderate disaster, or major disaster according to the scale proposed by Eshghi and Larson (2008), which basically compares the number of fatal and affected victims for a given disaster. The classification is put in ascending order of pessimism, i.e., emergency situation is the least pessimistic disaster in terms of total affected (or fatal) victims, while major disaster refers to the most pessimistic disaster type. The categorization for our real data is shown in the last column of Table 2.

Table 2: Floods and mass movements in the state of Rio de Janeiro between 1966 and 2013. (Source: Moreno et al. (2016)).

Year	Fatal Victims	Affected	Disaster type[1]
1990	7	800	Emergency situation
1992	25	1,000	Emergency situation
2013	30	1,510	Crisis situation
2001	50	1,946	Crisis situation
2003	7	2,000	Crisis situation
2013	2	2,000	Crisis situation
2007	6	2,272	Crisis situation
2008	9	50,953	Minor disaster
2010	256	74,938	Minor disaster
2013	4	200,000	Moderate disaster
2011	909	304,562	Moderate disaster
1988	289	3,020,734	Major disaster
1966	350	4,000,000	Major disaster

[1] Classification based on Eshghi and Larson (2008).

3. Bootstrap phase. We calculate the probability of occurrence of each type of disaster by using the Bootstrap method (Efron, 1979)attempting to incorporate extra variability in the small sample. Thus, $B = 1000$ random samples was generated from the original data in Table 2, each sample with 13 entries. For each sample $b = 1, ..., B$ we calculate the relative frequency and the average number of affected people for each type of disaster. Finally, the Bootstrap relative frequency was determined as $\frac{\sum_b f_b^a}{B}$, while the Bootstrap average number of affected people was evaluated as $\frac{\sum_b victim_b^a}{B}$, for $a \in A$, with $A = \{$ emergency situation, crisis situation, minor disaster, moderate disaster, major disaster $\}$.

   f_b^a is the relative frequency of disaster a in the sample b and $victim_b^a$ is the average number of affected people of disaster a in the sample b. Notice that this step provides not only the probability of the scenarios, but also the realizations for the total number of victims in each scenario. From the total number of victims, we estimate the number of victims per affected area based on its population density. As we are dealing with a multiperiod model, it is necessary to determine the number of victims per period (day). For this purpose, we used a random number generator based on a discrete uniform distribution that considers peaks of victims in some periods, as proposed in Alem et al. (2016). Finally, the victims needs are simply evaluated as follows. Water and personal hygiene kits, one for each victim; food and domestic hygiene kits, one for each 5 victims; medical kits, one for a group of 90 victims.

4. Scenarios evaluation. All random variables are assumed to be dependent on the type or

magnitude of the disaster. For example, worse disasters generate a higher number of victims (d), which increases the demand and supply of emergency commodities. Worse disasters are also assumed to result in fewer routes for trucks and helicopters, in more routes for boats, and in a decreased amount of usable inventory at relief centers. The amount of supplies in depots was randomly generated according to the number of the victims using a uniform distribution. Similarly, the usable inventory at relief centers was generated via a uniform distribution.

Then one scenario was considered for each type of disaster, totalling 5 scenarios. Each scenario consists of one different value (realization) for each stochastic parameter, e.g., scenario ‘emergency situation’ (#1) is represented by the vector $[\mathbf{q}^{\mathbf{1}}, \mathbf{p}^{\mathbf{1}}, \mathbf{d}^{\mathbf{1}}, \mathbf{a}^{\mathbf{1}}]$, with corresponding probability of occurrence given by π^1.

Table 3 summarizes the resulting scenarios and the demand and supply at each city. The demand on Table 3 corresponds to the number of victims requiring commodities at each a ected city (Teresópolis-TRS, Petrópolis-PTP, Nova Friburgo-NFR, São José do vale do Rio Preto-SJV, Bom Jardim-BJD). The supply corresponds to the number of victims for whom supply is available in the depots located in three cities (Teresópolis-TRS, Petrópolis-PTP, Nova Friburgo-NFR). Finally, the demand and supply of each type of commodity was generated based in the quantity of commodities required by each victim. For the sake of brevity, the detailed values are provided in the supplementary material.

Table 3: Stochastic data according to each disaster type.

			Number of affected people					
Scenario	Disaster type	Probability	TRS	PTP	NFR	SJV	BJD	Total (d)
1	Emergency situation	0.153850	220	382	238	27	34	901
2	Crisis situation	0.384600	476	827	512	58	73	1,946
3	Minor situation	0.153850	15,378	26,724	16,542	1,866	2,343	62,853
4	Moderate situation	0.153850	61,704	107,233	66,373	7,489	9,401	252,200
5	Major disaster[1]	0.153850	856,234	1,488,042	921,036	103,918	130,451	3,499,681

	Number of victims for whom supply is available					Avg. proportion of usable inventory	% of available routes		
Scenario	TRS	PTP	NFR	Total			Truck	Boat	Helicopter
1	536	233	144	913	$U(0.95, 1.05) \cdot d$	$U(0.85, 1.0)$	80%	20%	95%
2	1,122	488	302	1,912	$U(0.90, 1.10) \cdot d$	$U(0.80, 0.95)$	65%	30%	85%
3	38,223	16,607	10,279	65,109	$U(0.85, 1.15) \cdot d$	$U(0.75, 0.90)$	50%	40%	75%
4	155,607	67,607	41,846	265,060	$U(0.80, 1.20) \cdot d$	$U(0.70, 0.85)$	35%	50%	65%
5	2,199,353	955,559	591,451	3,746,363	$U(0.75, 1.25) \cdot d$	$U(0.65, 0.75)$	20%	60%	55%

[1] This is a hypothetical scenario assuming that 22% of the current population of the State of Rio de Janeiro is concentrated in the Serrana Region.

5.2. *Case Study*

The data set used in the computational tests are based on the 2011 Megadisaster in the Serrana region of Rio de Janeiro state in Brazil (Dourado et al., 2012; Rio De Janeiro, 2011). The base case was designed to be realistic, but due to the limited availability of information, some parameters were estimated from the literature (The Sphere Project, 2011; Alem et al., 2016; Moreno et al., 2016). The data constituted 3 depots (I) located in larger cities, 16 potential locations for relief centers (J), 5 affected areas (K) (cities), 5 emergency commodities (W) (food, domestic hygiene kits, personal hygiene kits, medical kits, and water), 3 types of vehicles (L) (trucks, boats, and helicopters), 5 scenarios (Ξ) (type of disasters) and a time horizon of 10 periods (days) with 240 micro-periods (hours). Further details of the parameters may be found in the supplementary material (Appendix A; see Tables A1−A5).

A total of 17 instances were generated from the base data to examine situations with higher supply; less supply; reduced capacity of relief centers; increased travel times; higher number of scenarios; and reduced number of available vehicles. The proposed instances are summarized in Table 4. The column $\max_w |\Delta_w|$ in Table 4 indicates the maximum deprivation time of the products considered in the instance. We considered three type of instances. The first type (I1-I5, I7-I8) considers all the depots and affected areas, but only the three products with higher priority (water, food, medical kits), the three less pessimistic scenarios (emergency situation, crisis situation, minor disaster), two types of vehicles (trucks, boats), and half of the total of relief centers available. The second type (I9-I13, I15-I17) considers all the depots, relief centers, affected areas, commodities, scenarios, and vehicles. The third type (I6, I14) refers to instances with 13 scenarios; in these cases, the remaining data is the same as in instances I1 and I9, respectively. The 13 scenarios correspond to the 13 past disaster events provided in Table 2. Such instances then have two ‘emergency situation’ scenarios, five ‘crisis situation’ scenarios, two ‘minor situation’ scenarios, two ‘moderate disaster’ scenarios, and two ‘major disaster’ scenarios. The stochastic data for these equiprobable scenarios were also generated according to the type/magnitude of the corresponding disaster, as shown in Table 3.

Table 4: Characteristics and dimensions of the proposed set of instances.

Instance	Characteristic	$\lvert I\rvert$	$\lvert J\rvert$	$\lvert K\rvert$	$\lvert W\rvert$	$\lvert T\rvert$	$\lvert\Theta\rvert$	$\lvert\Xi\rvert$	$\lvert L\rvert$	$\max_w \lvert\Delta_w\rvert$
I1	Base case	3	8	5	3	10	240	3	2	96
I2	I1 with q^{ξ}_{wit} increased 50%	3	8	5	3	10	240	3	2	96
I3	I1 with q^{ξ}_{wit} reduced 50%	3	8	5	3	10	240	3	2	96
I4	I1 with ρ_j and ρ'_{wj} reduced 100 times	3	8	5	3	10	240	3	2	96
I5	I1 with τ_{ijl} increased 5 times	3	8	5	3	10	240	3	2	96
I6	I1 with $\lvert\Xi\rvert = 13$	3	8	5	3	10	240	13	2	96
I7	I1 with $\phi_1 = 5, a^{\xi}_{ij2t} = 0$	3	8	5	3	10	240	3	2	96
I8	I1 with $\phi_2 = 5, a^{\xi}_{ij1t} = 0$	3	8	5	3	10	240	3	2	96
I9	Base case	3	16	5	5	10	240	5	3	120
I10	I9 with q^{ξ}_{wit} increased 50%	3	16	5	5	10	240	5	3	120
I11	I9 with q^{ξ}_{wit} reduced 50%	3	16	5	5	10	240	5	3	120
I12	I9 with ρ_j and ρ'_{wj} reduced 100 times	3	16	5	5	10	240	5	3	120
I13	I9 with τ_{ijl} increased 5 times	3	16	5	5	10	240	5	3	120
I14	I9 with $\lvert\Xi\rvert = 13$	3	16	5	5	10	240	13	3	120
I15	I9 with $\phi_1 = 5, a^{\xi}_{ij2t} = a^{\xi}_{ij3t} = 0$	3	16	5	5	10	240	5	3	120
I16	I9 with $\phi_2 = 5, a^{\xi}_{ij1t} = a^{\xi}_{ij3t} = 0$	3	16	5	5	10	240	5	3	120
I17	I9 with $\phi_3 = 5, a^{\xi}_{ij1t} = a^{\xi}_{ij2t} = 0$	3	16	5	5	10	240	5	3	120

5.3. Deprivation cost estimation

Different emergency commodities may have distinct priorities regarding victims needs, so two deprivation cost functions are proposed for high-priority commodities ($g_w(\delta) = g_w^{HP}(\delta)$) and for low-priority commodities ($g_w(\delta) = g_w^{LP}(\delta)$) as follows:

$$g_w^{HP}(\delta) = NP_w \cdot CM_w \cdot \frac{e^{1.5031+0.1172\cdot\delta} - e^{1.5031}}{e^{1.5031+0.1172\cdot|\Delta_w|} - e^{1.5031}}, \text{ and} \tag{25}$$

$$g_w^{LP}(\delta) = NP_w \cdot CM_w \cdot \frac{e^{0.065\cdot\delta} - 1}{e^{0.065\cdot|\Delta_w|} - 1}, \tag{26}$$

where NP_w is the number of people affected by the shortage of commodity w and CM_w is the maximum deprivation cost per person for commodity w.

Differently from Pérez-Rodríguez and Holguín-Veras (2015), our suggested deprivation cost function accounts for scales $\frac{NP_w\cdot CM_w}{e^{1.5031+0.1172\cdot|\Delta_w|}-e^{1.5031}}$ and/or $\frac{NP_w\cdot CM_w}{e^{0.065\cdot|\Delta_w|}-1}$ attempting to take into account the emergency commodities that serve more than one person. For example, one unit of food kit serves 5 people (approximately one family). In this context, the proposed scales ensure that after $|\Delta_w|$ micro-periods of deprivation, the total deprivation cost is equal to the maximum deprivation cost per person (CM_w) multiplied by the number of affected people (NP_w), e.g., $g_w^{LP}(|\Delta_w|) = NP_w \cdot CM_w \cdot \frac{e^{0.065\cdot|\Delta_w|}-1}{e^{0.065\cdot|\Delta_w|}-1} = NP_w \cdot CM_w$. The same rationale holds for high-priority commodities.

Maximum deprivation costs and times can thus be set for specific emergency commodities. For example, water and food are high-priority commodities with similar cost functions, but the deprivation time for water is lower than that for food. Maximum deprivation times do not need to be evaluated on a “death basis”. We prefer to use a less pessimistic reference for the maximum deprivation time because the time horizon is rather short (10 days) and we would like to encourage the demand fulfillment in the first few days after disaster strikes. Since the time horizon is usually short, the maximum deprivation time for low-priority commodities (domestic hygiene kits and personal hygiene kits) was set at 5 days (120 hours), whereas for high-priority commodities it was set at 3 days (72 hours) for water and 4 days (96 hours) for food and medical kits. Table 5 summarizes the selected values for NP_w, CM_w, $|\Delta_w|$ and $g_w(\delta)$ for each commodity. Figure 5 shows the deprivation cost functions $g_w(\delta)$ for the first 120 hours of deprivation time. Clearly, the functions are monotonic, non-linear, and convex with respect to the deprivation time δ, as recommended by the literature (Holguín-Veras et al., 2013; Pérez-Rodríguez and Holguín-Veras, 2015).

Table 5: Parameters and deprivation cost functions for the considered commodities.

w	Commodity	$\lvert\Delta_w\rvert$ (hours)	CMP_w[1] (BRL)	NP_w	$g_w(\delta)$[2]	$g_w(1)$ (BRL)	$g_w(\lvert\Delta_w\rvert)$ (BRL)
1	Water	72	140,000	1	$6.7404 \cdot Q^H(\delta)$	3.768	140,000
2	Food	96	140,000	5	$2.0229 \cdot Q^H(\delta)$	1.1308	700,000
3	Medical kits	96	140,000	90	$36.4128 \cdot Q^H(\delta)$	20.35	12,600,000
4	Personal hygiene kits	120	14,000	1	$1.2055 \cdot Q^L(\delta)$	0.3854	14,000
5	Domestic hygiene kits	120	14,000	5	$6.0275 \cdot Q^L(\delta)$	1.927	70,000

[1] Value based on Holguín-Veras et al. (2013).

5.4. Computational performance of the solution approaches

The proposed instances I1−I17 were solved via the approaches developed in Section 4. Table 6 summarizes how each solution method was tested, focusing on the maximum allowed elapsed times for each strategy. Even though all the methods use either the linear or the mixed-integer linear programming CPLEX solver at some step, we use the term “CPLEX” strategy to emphasize

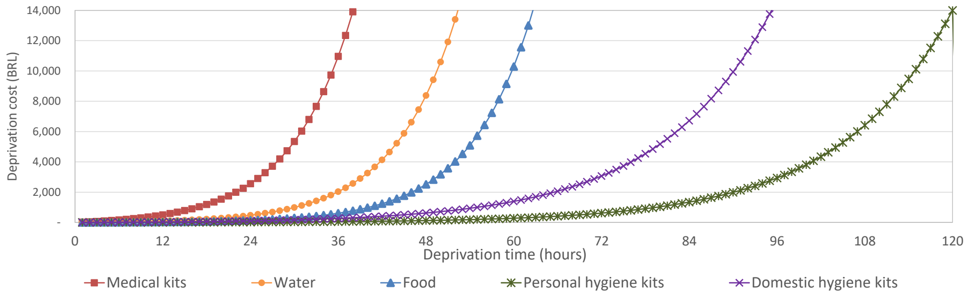

Figure 5: Deprivation cost functions $g_w(\delta)$.

the approach in which the monolithic model is directly solved by this solver without any proposed heuristic.

Table 6: Summary of the solution strategies.

Strategy	Description	Maximum elapsed time
CPLEX	Level 1: CPLEX to solve FLTP minimizing f^{DC}	3,600 seconds
	Level 2: CPLEX to solve FLTP minimizing f^{LC}	3,600 seconds
FXO	Level 1: FXO to solve FLTP minimizing f^{DC}	360 seconds for each subproblem, totalling 3,600 seconds for the first level
	Level 2: FXO to solve FLTP minimizing f^{LC}	360 seconds for each subproblem, totalling 3,600 seconds for the second level
TSH	Level 1: CPLEX to solve ALTP minimizing f^{DC}	3,600 seconds
	Level 2: CPLEX to solve ALTP minimizing f^{ALC}	3,600 seconds
TSH+FXO	Level 1: CPLEX to solve ALTP minimizing f^{DC}	3,600 seconds
	Level 2: CPLEX to solve ALTP minimizing f^{ALC} and FXO to solve FLTP minimizing f^{LC}	360 seconds for each subproblem, totalling 3,600 seconds for the second level

We also analyzed some alternative configurations of CPLEX 12.5, such as turning off cutting planes, setting the frequency for invoking RINS heuristic to be after every 10 nodes, setting best-bound search for node selection and branching on the variable with minimum infeasibility for variable selection, and the MIP emphasis on feasibility. Under this alternative configuration, average elapsed times improved around 2% for the minimization of F^{DC} in the first level and optimality gaps improved up to 5% for the minimization of F^{LC} in the second level of the hierarchical method. This alternative configuration was thus used in all the remaining tests.

Table 7 shows the main results regarding objective function values, optimality gaps, and elapsed times for all solution approaches. The gap is computed as gap= $\frac{Z^h - Z^l}{Z^h}$, where Z^h is the objective function of the incumbent solution provided by the corresponding method and Z^l is the best lower bound. In most instances, the lower bound is the solution given by the linear relaxation. In a few instances, though, the lower bound was improved by CPLEX. The results suggest that it is easier to solve the first level subproblem, i.e., the minimization of the total deprivation costs, than the minimization of the logistics costs in the second level. Only two (three) instances were not solved by the CPLEX (FXO) strategy within gaps of less than 1% in the first level of the hierarchical model. In these cases, it was not possible to solve the second level model. Average elapsed times to solve the corresponding first level model by CPLEX, FXO, and TSH strategies were 458.6, 571.3 and 16.88 seconds, respectively. For the second level, it is clear that FXO strategy provides better results than CPLEX, since average gaps were reduced from 97.09% with CPLEX to 76.85% with FXO. The two-step heuristic TSH is more efficient to solve the hierarchical model at both levels than CPLEX and FXO. In fact, at the first level, TSH improved the results given by CPLEX and FXO strategies by 99.86% and 99.72% (on average), respectively. At the second level, TSH yielded solutions with an average improvement of 52.81% and 40.38% in comparison to the CPLEX and FXO strategies, respectively. In addition, TSH presented elapsed times significantly lower than CPLEX and FXO. The hybrid heuristic was the strategy that most improved optimality gaps in the second level model, but at the expense of increasing elapsed times. In the second level, average gaps decreased from 45.82% with TSH to 33.66% with TSH+FXO, whereas elapsed times increased by 70.68%.

The comparative performance of the proposed methods were evaluated via performance profiles. Roughly speaking, performance profiles are based on the cumulative distribution function $P(f, q)$, which indicates the probability of a given method being within a factor $2^q \in R$ from the best possible ratio (Dolan and Moré, 2002). Table 8 exhibits the extreme values of the performance profiles. For the first level, the heuristic TSH achieved the best elapsed time for 100% of instances and the best gap for 94% of instances. In the 6% remaining instances, TSH still provides a gap within a factor of $2^{0.2088} \approx 1.15$ times the best solution found. For the second level, the hybrid heuristic (TSH+FXO) achieved the best gap for 100% of the instances, but the best elapsed time was found only for 17.65% of the instances. Although heuristic TSH was the fastest strategy for 100% of the instances in the second level, it performed badly regarding optimality gaps, being within a factor of $2^{1.957} \approx 3.88$ times the best solutions of the hybrid strategy.

In summary, the best strategy to find an acceptable solution in a short time is TSH at both levels of the hierarchical model. However, if the decision-maker is able to accept longer computational times, thus having tighter optimality gaps, the hybrid strategy TSH+FXO should be used at the second level of the hierarchical model. The results of the remaining sections refer to the solutions obtained by the hybrid heuristic.

Table 7: Objective functions, gaps and computational times of the instances solved by CPLEX, FXO, TSH, and TSH+FXO.

	CPLEX to solve f^{DC} and CPLEX to solve f^{LC}						FXO to solve f^{DC} and FXO to solve f^{LC}					
Instance	Objective f^{DC}	GAP (%) f^{DC}	Time (sec.) f^{DC}	Objective f^{LC}	GAP (%) f^{LC}	Time (sec.) f^{LC}	Objective f^{DC}	GAP (%) f^{DC}	Time (sec.) f^{DC}	Objective f^{LC}	GAP (%) f^{LC}	Time (sec.) f^{LC}
I1	1,884,647,953	-	11.69	217,470,000	99.92	3,600	1,884,685,874	0.0020	24.17	581,520	71.03	3,600
I2	414,349,258	-	10.16	215,433,440	99.99	3,600	414,368,837	0.0047	22.60	181,297	83.06	3,600
I3	18,438,464,297	-	11.70	212,742,688	99.99	3,600	18,438,780,407	0.0017	25.35	130,921	80.56	3,600
I4	3,137,503,511	-	10.61	190,442,140	99.92	3,600	3,146,843,321	0.2968	133.7	1,140,342	86.28	3,600
I5	1,887,739,361	-	12.06	331,078,444	99.95	3,600	1,887,767,063	0.0017	21.33	525,252	69.76	3,600
I6	59,844,338,823	-	52.35	97,972,871	85.70	3,600	60,454,215,401	1.009	22.31	NA	NA	NA
I7	1,884,655,205	-	9.594	116,160,530	99.96	3,600	1,884,864,360	0.0111	21.34	128,083	60.33	3,600
I8	1,884,917,104	-	7.754	5,425,645	86.02	3,600	1,885,008,062	0.0048	20.70	2,556,343	70.33	3,600
I9	1,200,244,938	-	78.48	7,871,008,344	99.94	3,600	1,204,969,728	0.3921	278.9	28,186,432	82.79	3,600
I10	240,855,887	-	69.05	7,278,023,436	99.99	3,600	244,057,995	1.312	792.7	NA	NA	NA
I11	506,579,850,356	-	68.94	7,699,910,209	99.99	3,600	509,133,052,562	0.5015	288.0	2,500,692	86.28	3,600
I12	851,704,705,937	9.958	3,600	NA	NA	NA	768,320,300,236	0.1858	3,600	2,354,933	84.74	3,600
I13	1,225,147,845	-	87.91	8,513,737,411	99.94	3,600	1,231,652,031	0.5281	124.0	20,069,619	72.55	3,600
I14	112,029,523,846	98.93	3,600	NA	NA	NA	2,374,148,099	49.60	3,600	NA	NA	NA
I15	1,200,416,830	-	61.56	43,558,629	96.03	3,600	1,209,533,388	0.7537	285.3	12,596,862	86.28	3,600
I16	1,200,326,604	-	54.35	275,167,394	90.68	3,600	1,204,673,674	0.3609	279.2	93,087,066	72.46	3,600
I17	1,200,244,938	-	50.78	6,602,294,760	98.29	3,600	1,200,498,512	0.0211	172.1	368,712,939	69.43	3,600
Average	92,115,172,511	6.405	458.6	2,644,695,063	97.09	3,600	80,948,201,150	3.2348	571.3	38,053,736	76.85	3,600

	TSH to solve f^{DC} and TSH to solve f^{LC}						TSH to solve f^{DC} and TSH+FXO to solve f^{LC}					
Instance	Objective f^{DC}	GAP (%) f^{DC}	Time (sec.) f^{DC}	Objective f^{LC}	GAP (%) f^{LC}	Time (sec.) f^{LC}	Objective f^{DC}	GAP (%) f^{DC}	Time (sec.) f^{DC}	Objective f^{LC}	GAP (%) f^{LC}	Time (sec.) f^{LC}
I1	1,884,647,953	-	*3.213*	212,578	20.76	*6.319*	1,884,647,953	-	*3.213*	**202,145**	**16.67**	3,600
I2	414,349,258	-	*2.464*	85,771	64.19	*18.83*	414,349,258	-	*2.464*	**48,767**	**37.03**	3,600
I3	18,438,464,297	-	*3.385*	66,392	61.66	*14.23*	18,438,464,297	-	*3.385*	**37,604**	**32.31**	3,600
I4	3,137,503,511	-	*2.870*	211,169	25.93	*11.64*	3,137,503,511	-	*2.870*	**184,589**	**15.26**	3,600
I5	1,887,735,813	-	*4.352*	235,575	32.57	*5.055*	1,887,735,813	-	*4.352*	**194,533**	**18.34**	2,825
I6	**59,937,667,329**	**0.1557**	*18.00*	20,111,064	30.35	*18.24*	59,937,667,329	**0.1557**	*18.00*	**19,373,125**	**27.70**	3,600
I7	1,884,655,205	-	*3.042*	116,754	56.48	*30.47*	1,884,655,205	-	*3.042*	**68,087**	**25.38**	3,600
I8	1,884,917,104	-	*2.013*	1,231,914	38.43	*13.60*	1,884,917,104	-	*2.013*	**841,786**	**9.902**	3,600
I9	1,200,244,938	-	*22.12*	5,723,634	15.23	*1,639*	1,200,244,938	-	*22.12*	**5,597,819**	**13.32**	3,600
I10	240,855,887	-	*18.05*	2,422,413	62.04	*652.1*	240,855,887	-	*18.05*	**2,419,974**	**62.00**	3,600
I11	506,579,850,356	-	*34.40*	1,510,139	77.28	*1,728*	506,579,850,356	-	*34.40*	**1,508,601**	**77.25**	3,600
I12	766,892,911,524	-	*26.01*	**1,413,271**	**74.57**	*3,600*	766,892,911,524	-	*26.01*	**1,413,271**	**74.57**	*3,600*
I13	1,225,147,845	-	*38.07*	6,847,308	19.53	*1,127*	1,225,147,845	-	*38.07*	**6,634,392**	**16.95**	3,600
I14	1,196,459,215	-	*53.68*	**50,084,074**	**84.44**	*3,600*	1,196,459,215	-	*53.68*	**50,084,074**	**84.44**	*3,600*
I15	1,200,416,830	-	*19.03*	3,567,868	51.55	*3,600*	1,200,416,830	-	*19.03*	**2,724,136**	**36.54**	*3,600*
I16	1,200,327,194	-	*17.25*	35,799,073	28.39	*526.6*	1,200,327,194	-	*17.25*	**28,343,261**	**9.554**	3,600
I17	1,200,244,938	-	*19.06*	174,747,814	35.50	*921.8*	1,200,244,938	-	*19.06*	**132,483,645**	**14.92**	3,600
Average	**80,612,141,129**	**0.0092**	*16.88*	17,905,106	45.82	*1,030*	80,612,141,129	**0.0092**	*16.88*	**14,832,930**	**33.66**	3,571

NA: Not available because the gap of the first-level is greater than 1%. For this reason, the second-level is not solved.
Best results for gaps and objective functions. *Best results for elapsed times.*

Table 8: Extreme values of the performance profile for the proposed solution methods.

Solution method	First level f^{DC} GAP $P(f,q)$	First level f^{DC} GAP q	First level f^{DC} Time $P(f,q)$	First level f^{DC} Time q	Second level f^{LC} GAP $P(f,q)$	Second level f^{LC} GAP q	Second level f^{LC} Time $P(f,q)$	Second level f^{LC} Time q
CPLEX to solve f^{DC} and CPLEX to solve f^{LC}	0.8824	6.643	–	7.113	–	3.247	0.1765	9.476
FXO to solve f^{DC} and FXO to solve f^{LC}	–	5.661	–	7.113	–	2.923	0.1765	9.476
TSH to solve f^{DC} and TSH to solve f^{LC}	**0.9412**	**0.2088**	*1.000*	-	0.1176	1.957	*1.000*	-
TSH to solve f^{DC} and TSH+FXO to solve f^{LC}	**0.9412**	**0.2088**	*1.000*	-	**1.000**	**-**	0.1765	9.154

Values of $P(f,q)$ when $q=0$. Fraction of instances for which the strategy reached the best solution (in GAP or time).
Values of q when $P(f,q)=1$. The solution achieved by the strategy is within a factor of 2^q of the best approach.
Best results for gaps and objective functions. *Best results for elapsed times.*

5.5. Benefit of the proposed approach

Here, we discuss the performance of our approach in terms of: (i) reusing vehicles; (ii) deprivation costs; (iii) prioritizing deprivation over logistics costs. In the first case (i), we compare the solutions with total multiple trips to the solution with the possibility of performing partial multiple trips only within each period. We call this strategy WP ("within period"). The comparison between multiple and single trips in a similar context is discussed in Moreno et al. (2016). In the second case (ii), we compare the model with deprivation costs to a similar model where deprivation costs are replaced by a static penalty equal to the maximum deprivation cost per person, i.e., $g_w(\delta) - g_w(\delta - 1) = CM_w$, for all $\delta,\ w$. This last equality shows that the penalty for unsatisfied demand is the same regardless of how long a victim is deprived of an emergency commodity. We call this strategy WCP ("worst-case penalty"). We performed preliminary computational experiments with other penalty values, such as that in Moreno et al. (2016, 2017) which used as penalty 10 times the commercial value of the product and Holguín-Veras et al. (2013), which used values between \$50 and \$5,000,000 for "human life valuation". However, the overall computational results were similar for the bi-objective model, in which the deprivation cost does not compete with logistic costs. Finally, the last case (iii) aims to show the impact of modelling a bi-objective function to prioritize deprivation costs instead of using a mono-objective function, as proposed in the seminal paper of Holguín-Veras et al. (2013).

5.5.1. Impact of deprivation costs

The impact of the deprivation costs is evaluated according to three main aspects or performance measures: amount of unmet demand in the last period of the time horizon; fairness in distribution; and deprivation times. In order to compare fairness between two distribution policies, the tests analyze the standard deviation across unmet demands per affected area and the worst-case scenario for the distribution. Tables 9 and 10 shows those performance measures obtained with and without the consideration of the deprivation costs.

Table 9: Costs, main decisions, and service levels for all the proposed instances from FLTP, WCP, and WP (Instances I1-I8).

				1º Stage Decisions		2º Stage Decisions			Unmet demand by a. area (k)			Service level by affected area (k)			
Instance	Model	Logistic cost ($f^L C$)	Deprivation cost ($f^D c$)	# Relief centers	# Vehicles	# Vehicles	Inventory	Total shortage	Total	Average	Standard deviation	Mean	Standard deviation	Worst	Best
I1	FLTP	202,145	1,884,647,954	4	28	11	–	23,710	99	20	24	99.50	0.0064	98.28	100.0
	WCP	181,760	30,575,205,991	3	21	14	–	23,043	319	64	81	97.37	0.0456	88.27	100.0
	WP	205,958	1,884,647,954	3	29	12	–	23,705	99	20	22	99.50	0.0064	98.27	100.0
I2	FLTP	48,767	414,349,259	2	7	1	–	7,062	10	2	4	99.89	0.0021	99.47	100.0
	WCP	48,559	4,957,656,172	2	4	3	–	7,061	10	2	4	99.89	0.0021	99.47	100.0
	WP	82,871	414,349,259	2	13	5	–	7,061	10	2	4	99.89	0.0021	99.47	100.0
I3	FLTP	37,604	18,438,464,298	2	4	2	–	21,372	21,370	4,274	3,745	31.45	0.3499	0.028	88.14
	WCP	27,640	182,422,253,029	2	3	–	-	21,370	21,370	4,274	3,747	29.95	0.3646	–	88.24
	WP	53,218	18,438,464,298	2	7	4	–	21,374	21,370	4,274	3,757	29.51	0.3692	–	88.57
I4	FLTP	184,589	3,137,503,512	8	15	16	–	28,524	4,655	931	902	84.33	0.0905	72.77	100.0
	WCP	188,357	41,626,799,409	8	13	19	–	28,046	5,015	1,003	942	81.94	0.1213	62.65	100.0
	WP	210,318	3,137,521,665	8	18	19	–	28,524	4,655	931	903	84.34	0.0905	72.77	100.0
I5	FLTP	194,533	1,887,735,814	3	28	10	–	23,703	99	20	21	99.51	0.0058	98.39	100.0
	WCP	164,866	37,963,018,232	3	14	18	–	21,851	618	124	149	96.79	0.0442	88.27	100.0
	WP	192,972	1,887,738,124	3	29	9	40	23,708	99	20	20	99.50	0.0058	98.40	100.0
I6	FLTP	19,373,125	59,937,667,330	6	1,102	2,551	204	1,956,835	270,955	54,191	43,232	92.50	0.0403	86.54	98.92
	WCP	14,550,058	715,761,919,078	6	1,063	1,598	81,480	1,986,380	271,238	54,248	42,911	92.51	0.0400	86.56	98.88
	WP	20,207,716	63,803,759,307	6	1,156	2,695	–	1,997,745	310,715	62,143	56,899	91.98	0.0434	86.98	98.88
I7	FLTP	68,087	1,884,655,206	2	5	9	–	23,705	99	20	21	99.49	0.0062	98.31	100.0
	WCP	65,847	30,916,823,613	2	5	8	–	23,043	319	64	81	97.37	0.0456	88.27	100.0
	WP	102,523	1,884,655,206	2	5	19	–	23,705	99	20	21	99.51	0.0062	98.31	100.0
I8	FLTP	841,786	1,884,917,105	4	5	153	–	23,706	99	20	19	99.48	0.0055	98.44	100.0
	WCP	765,606	32,020,553,167	3	5	139	–	23,043	319	64	81	97.37	0.0456	88.27	100.0
	WP	1,184,654	1,884,917,105	4	5	220	–	23,704	99	20	21	99.51	0.0061	98.33	100.0

Table 10: Costs, main decisions, and service levels for all the proposed instances from FLTP, WCP, and WP (Instances I9-I17).

				1º Stage Decisions		2º Stage Decisions			Unmet demand by area (k)			Service level by area (k)			
Instance	Model	Logistic cost ($f^L C$)	Deprivation cost ($f^D c$)	# Relief centers	# Vehicles	# Vehicles	Inventory	Total shortage	Total	Average	Standard deviation	Mean	Standard deviation	Worst	Best
I9	FLTP	5,597,819	1,200,244,939	9	207	1,067	0	1,816,796	39	8	10	99.99	0.0001	99.99	100.0
	WCP	5,472,721	112,410,469,490	8	322	918	–	1,816,796	39	8	10	100.00	0.0001	99.99	100.0
	WP	6,080,091	1,200,244,939	9	407	1,015	–	1,816,813	39	8	10	99.99	0.0001	99.99	100.0
I10	FLTP	2,419,974	240,855,888	9	346	309	–	351,362	9	2	3	100.00	0.0000	100.00	100.0
	WCP	2,091,333	12,627,834,435	7	241	319	–	351,357	9	2	3	100.00	0.0000	100.00	100.0
	WP	2,571,259	240,855,888	9	345	375	–	351,362	9	2	3	100.00	0.0000	100.00	100.0
I11	FLTP	1,508,601	506,579,850,357	9	175	242	–	1,857,244	1,857,227	371,445	533,043	63.56	0.2332	26.16	96.34
	WCP	1,274,102	4,821,876,243,758	7	184	168	–	1,857,227	1,857,227	371,445	525,050	62.21	0.2333	26.88	95.12
	WP	1,618,743	506,579,850,357	9	198	252	–	1,857,244	1,857,227	371,445	531,502	62.93	0.2361	26.38	97.05
I12	FLTP	1,413,271	766,892,911,525	16	118	47	446	4,353,851	4,249,700	849,940	649,383	8.48	0.0395	4.64	16.11
	WCP	2,492,854	6,917,635,210,097	16	127	44	–	4,346,256	4,249,989	849,998	649,707	8.43	0.0382	4.53	15.74
	WP	4,982,744	766,893,443,410	16	133	61	–	4,350,829	4,249,700	849,940	649,170	8.38	0.0372	4.62	15.51
I13	FLTP	6,634,392	1,225,147,846	8	629	960	6,634	1,816,802	39	8	10	99.99	0.0001	99.99	100.0
	WCP	6,083,002	320,951,979,541	8	613	795	139,680	1,816,796	39	8	10	100.00	0.0001	99.99	100.0
	WP	6,798,185	1,225,147,846	6	612	1,019	–	1,816,797	39	8	10	99.99	0.0001	99.99	100.0
I14	FLTP	50,084,074	1,196,459,216	12	1,000	2,446	–	3,867,004	126	25	31	99.99	0.0001	99.98	100.0
	WCP	103,348,483	261,864,765,078	13	3,000	1,966	–	3,796,807	23,525	4,705	9,347	99.87	0.0024	99.39	100.0
	WP	50,027,770	1,196,459,216	12	1,012	2,562	–	3,867,004	126	25	31	99.99	0.0001	99.98	100.0
I15	FLTP	2,724,136	1,200,416,831	7	10	733	133	1,816,802	39	8	6	99.99	0.0001	99.99	100.0
	WCP	2,513,545	119,706,140,838	7	10	665	24,603	1,816,796	39	8	10	100.00	0.0001	99.99	100.0
	WP	3,253,471	1,200,416,831	8	10	892	–	1,816,796	39	8	10	99.99	0.0001	99.99	100.0
I16	FLTP	28,343,261	1,200,327,195	10	10	5,584	2,167	1,816,796	39	8	6	100.00	0.0000	99.99	100.0
	WCP	27,877,182	115,035,968,341	10	10	5,484	154,549	1,816,796	39	8	6	100.00	0.0000	99.99	100.0
	WP	37,262,671	1,200,327,195	10	10	7,369	–	1,816,796	39	8	7	100.00	0.0000	99.99	100.0
I17	FLTP	132,483,645	1,200,244,939	11	10	1,578	–	1,816,796	39	8	10	99.99	0.0001	99.99	100.0
	WCP	142,603,841	112,410,469,490	10	10	9,189	269,381	1,816,796	39	8	10	100.00	0.0001	99.99	100.0
	WP	198,174,579	1,200,244,939	11	10	9,189	–	1,816,796	39	8	10	99.99	0.0001	99.99	100.0
Average*	FLTP	14,832,930	80,612,141,130	7	218	925	564	1,271,886	376,744	75,349	72,380	86.95	0.0459	81.35	94.09
	WCP	18,220,574	815,927,253,515	7	332	1,256	39,394	1,268,792	378,244	75,649	72,479	86.10	0.0578	78.38	94.00
	WP	19,588,808	80,839,590,796	7	235	1,513	2	1,274,115	379,083	75,817	73,082	86.77	0.0473	81.38	94.12

* Average considering all the instances (I1-I17) .

Overall results indicate that average service levels are higher when deprivation costs are considered. Moreover, deprivation costs help to reduce the standard deviation of the service levels evaluated across affected areas in 7 instances. The remaining instances experience similar standard deviations with or without deprivation costs. Interestingly, 6 of 7 instances − I1, I3, I4, I5, I7, and I8 − refer to examples consisting of only the three less pessimistic scenarios, i.e., emergency situation, crisis situation, and minor disaster. These scenarios exhibit lower total demands in comparison to the most pessimistic scenarios (moderate and major disaster) and, consequently, a lower flow of commodities as well. This result suggests that the distribution policy without deprivation costs often neglects scenarios with lower demands, which are particularly pronounced in smaller cities, such as São José do Vale do Rio Preto (SJV) and Bom Jardim (BJD).

For example, the total demand of victims located in SJV in the emergency situation scenario for instance I1 consists of 15 units of water, 3 units of food, and 1 medical kit. This rather low demand is not satisfied until the end of the humanitarian operations without deprivation costs, since the distribution policy prioritizes the cover of (higher) demand of bigger cities, such as Petrópolis (PTP), Teresópolis (TRP), and Nova Friburgo (NFR). In this case, the overall logistics costs are more important for determining the distribution policy than the fact that some areas have not received emergency aid for a longer period. On the other hand, the distribution of emergency commodities reaches SJV in the presence of deprivation costs because the corresponding shortage penalty increases exponentially with time in this case. As a consequence, the distribution prefers to fulfill (smaller) demand but from more affected areas as soon as possible, instead of satisfying more demand from less affected areas.

This result is particularly clear when analysis show that the average minimum service level per affected area is around 4% better when deprivation costs are used. In some instances, though, the improvement was more pronounced, e.g., 16.17% in instance I4 and 11.35% in instance I1. Moreover, when the external supplies are reduced in instance I3, none of the demand of SJV was satisfied without deprivation costs; however, this affected area may receive 56 emergency commodities if deprivation costs are taken into account. Even though this amount of delivery is negligible from the commercial supply chain perspective, it indicates that more affected areas can be covered by relief teams even under a lack of resources, when deprivation times are prioritized over pure logistics costs, which is in line with the spirit of humanitarian logistics.

On average, the standard deviation of service levels per affected area is almost 21% lower with deprivation costs. In some instances, though, this performance measure is much improved with deprivation costs, e.g., instance I14 experienced a standard deviation reduction by more than 95% mainly because 23,399 more emergency commodities were delivered. Without deprivation costs, though, the distribution policy in instance I14 prioritizes the delivery of food and medical kits over water (similar to the behaviour of the results of the instance I6). Clearly, without deprivation costs, the "urgent need" of aid is not taken into account, and for this reason, the distribution may prefer to focus on less urgent aid where the corresponding logistics costs are cheaper or the worst-case penalty is higher. This behaviour is particularly pronounced in instance I14 due to its characteristics, such as 5 emergency aid commodities and 13 scenarios. However, in real humanitarian operations, water should be delivered faster than the remaining emergency aid due its deprivation time, which is naturally enforced with our proposed model.

Deprivation costs also yield more effective solutions in terms of response and coverage. In fact, a total amount of 1,501 more emergency commodities were fulfilled until the last period of the time horizon with deprivation costs. Moreover, the total amount of aid delivered with deprivation costs is greater than or equal to the corresponding solution without deprivation costs for all the proposed instances. On the other hand, to provide a more effective distribution in an attempt to cover more affected areas and victims as soon as possible, the solution with deprivation costs usually postpones more emergency aid than the solution without deprivation. However, the time extension of such emergency aid postponement is much worse without deprivation costs. Table 11 shows the difference between the total amount of postponed emergency aid with and without deprivation costs. This difference is evaluated for time extensions in the following intervals, given in hours: $[1, 24]$, $[25, 48]$, $[49, 72]$, $[73, 96]$, and $[97, 120]$. Note that there is a greater amount of postponed emergency aid until 24 hours when deprivation costs are considered. However, as expected, deprivation costs help to mitigate the wait time of the victims for meeting their needs as time goes by. In this case, there is less postponed aid after 24 hours because the corresponding deprivation cost is extremely high. The rationale behind the fact that the model with deprivation costs postpones more emergency aid in the first 24 hours, in comparison to the model under worst-case penalty, is based on the manner in which shortages are penalized in each approach. Under worst-case penalty, for example, the penalty incurred for postponing 1 unit of water for 25 hours (BRL 3,500,000) is smaller than when postponing 5 units of food for 1 hour (BRL 4,200,000). When deprivation cost is considered, the penalty for postponing 1 unit of water for 25 hours (BRL 537.18) is higher than the penalty for postponing 5 units of food for 1 hour (BRL 5.65). In this case, the worst-case penalty approach postpones a total amount of 1 unit of water for 25 hours, whereas the deprivation cost model postpones 5 units of food for 1 hour. From the human suffering point of view, there is no doubt that it is much worse to wait 25 hours for water than 1 hour for food.

Table 11: Absolute difference in terms of shortage of commodities between models FLTP and WCP.

	$\#WCP$-$\#FLTP$				
Instance	$1-24$ hours	$25-48$ hours	$49-72$ hours	$73-96$	$97-120$ hours
I1	$-30{,}525$	23,636	6,242	96	NA
I2	-1	$-$	$-$	12	NA
I3	$-3{,}428$	1,377	1,432	$-1{,}298$	NA
I4	$-27{,}338$	20,210	9,843	25	NA
I5	$-35{,}927$	15,344	15,751	48	NA
I6	253,916	192,241	20,189	5,024	NA
I7	$-26{,}603$	19,458	5,998	25	NA
I8	$-19{,}586$	11,829	5,944	72	NA
I9	$-2{,}855$	2,912	178	48	$-$
I10	5	$-$	$-$	23	$-$
I11	2,044,001	38,170	420,571	477,827	314,883
I12	$-119{,}183$	16,419	20,245	$-66{,}982$	49,004
I13	$-80{,}710$	59,594	21,346	96	$-$
I14	$-3{,}862{,}454$	3,089,194	679,658	$-$	$-$
I15	$-17{,}461$	17,050	548	1	$-$
I16	279,578	52,780	2,176	96	$-$
I17	-69	43	25	1	$-$
Total	$-1{,}648{,}639$	3,560,258	1,210,146	415,113	363,887
Average	$-96{,}979$	209,427	71,185	24,418	40,432
Maximum	2,044,001	3,089,194	679,658	477,827	314,883
Minimum	$-3{,}862{,}454$	$-$	$-$	$-66{,}982$	$-$

[1] $\#FLTP$: Shortage of commodities in FLTP model according to the deprivation time; $\#WCP$: Shortage of commodities in WCP approach according to the deprivation time.
$-$ This symbol is used when the shortage of commodities in both models is equal.
NA: Not Available.

Deprivation costs often change the structure of (sub)optimal solutions. To take advantage of deprivation times, thus improving fairness in distribution, there is a clear trend in opening more relief centers in some instances (I1, I8, I9, I10, I11, and I17) in order to avoid shortages for longer periods of time as much as possible. In both cases, with our without deprivation costs, inventory levels are rather low because of the stock losses, and mostly used to reduce logistics costs. Apparently, higher inventory levels lead to fewer number of vehicles assigned in the second-stage, which makes sense because this pre-positioned "safe stock" can be delivered using some vehicles already contracted in previous periods, avoiding contracting more vehicles to perform trips between depots and relief centers where this safe stock is placed.

In general terms, the results of the FLTP model are in line with results in the literature (Holguín-Veras et al., 2013; Pérez-Rodríguez and Holguín-Veras, 2015). The use of deprivation costs makes sense only in a situation of scarcity. For example, instances with a higher number of supplies (I2,I10) present the smallest difference between the models with deprivation cost (FLTP) and without deprivation cost (WCP), as shown in Tables 9, 10 and 11. The use of social cost leads to delivery strategies with fairness in distribution amongst all affected areas. Social costs thus, show the importance of handling disaster situations in a multi-period approach. The numerical analysis indicates that exponentially increasing deprivation cost functions produce results that mitigate the total deprivation time compared with a constant penalty function, as also concluded in Pradhananga et al. (2016).

5.5.2. Impact of multiple trips

Not surprisingly, the possibility of performing multiple trips over the time horizon helps to decrease logistics costs, in fact by 24%, on average, mainly because the fixed cost of vehicles decreases substantially. Without multiple trips, it is necessary to hire 8% more vehicles at the first-stage and up to 60% more vehicles at the second-stage. Not performing multiple trips also deteriorates overall service levels in instances I4, I5, I6, and I12. The shortage of commodities in these instances consists of an average of 2,339 more commodities than in the original model. Worse shortages occur when travel times of some routes are longer than one day (instance I5), which implies not traversing this route and, consequently, not delivering the emergency commodities to the corresponding relief centers without reusing vehicles.

In instances I4, I6, and I12, it is not possible to perform distribution of commodities in a given period due to the limited capacity of relief centers. In model FLTP, though, this issue is overcome by scheduling new departures of vehicles to arrive in the first micro-periods of future periods − when there is available capacity − which is not possible when the option of multiple trips is not allowed. For instances I4, I5, and I12, deprivation costs without multiple trips are only slightly worse (less than 0.01%). On the other hand, not performing extra trips deteriorates deprivation costs by 6.45% in instance I6. Since the number of vehicles is not limited in the second-stage, the prohibition of multiple trips did not cause huge differences in deprivation costs. However, when the number of vehicles is bounded in both stages, not reusing vehicles might increase deprivation costs.

Vehicle scheduling with and without the option of multiple trips is illustrated in Figure 6 for instance I6. More than 35% of departures occur in the first hour of each day. The peaks in hours 7, 13, and 19 indicate that most vehicles return to depots to perform new departures. There are also departures from depots to relief centers in the last hours (21-24) of the days, which is not possible without performing multiple trips. In this case, there are no arrivals in relief centers in the first 2 hours of the days due to travel times, which deteriorates overall service levels. In particular, instance I6 presents a higher amount of unmet demand when multiple trips over the time horizon are not allowed (almost 40,000 units higher), which increases deprivation costs.

The results also suggested that keeping an inventory of emergency aid at some relief centers might be a good strategy to take advantage of vehicle capacity in the context of multiple trips. This phenomenon was particularly evidenced in instances I6, I12, I13, I15, and I16. In the single trip approach, more vehicles are assigned to increase the capacity of the fleet, which is particularly important in periods of higher demand. In this case, it is possible to reduce overall transportation costs via acquisition of an extra number of vehicles, thus avoiding keeping emergency aid in stock, as seen in instances I9-I17. Finally, note that multiple trips encourage the usage of more expensive vehicles, such as helicopters, as these vehicles present shorter travel times and so can be reused more times. Their use may help to reduce deprivation times in collapsed areas.

5.5.3. Mono- and Bi-objective Approaches

The idea of using a bi-objective model via a bi-level hierarchical procedure is to prioritize the minimization of deprivation costs in such a way this first-level objective is “infinitely

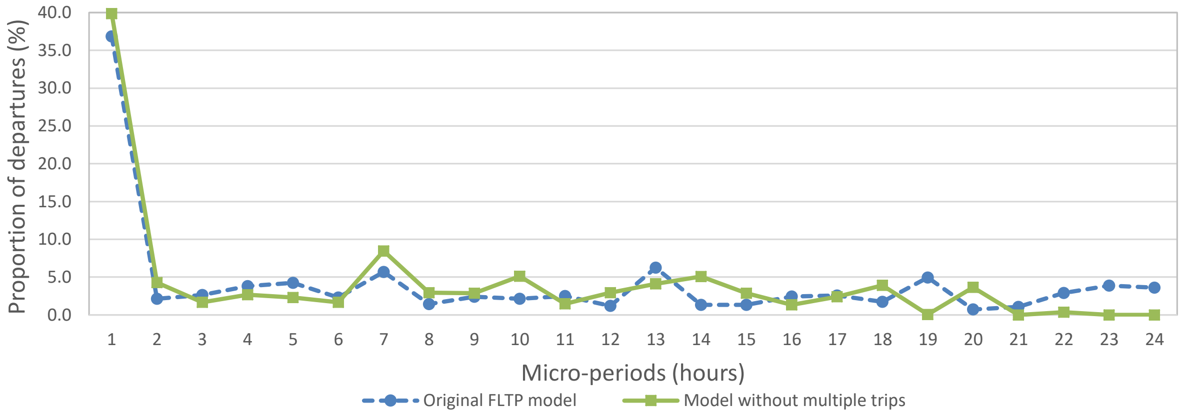

Figure 6: Proportion of departures from depots in the hours of the days ($\frac{\text{Number of departures at each hour of the day}}{\text{Total of departures}}$).

more important" than the minimization of the second-level logistics costs objective. However, the original idea of *social costs* proposed by Holguín-Veras et al. (2013) is to consider both deprivation and logistics costs in the same objective function. In an attempt to analyze the impact of optimizing both costs simultaneously, we present the results of the corresponding mono-objective problem (MFLTP) with the following structure: min $f^{LC} + f^{DC}$. Tables 12 and 13 show the detailed solutions provided by both approaches in terms of overall costs, logistics costs, deprivation costs, lost demand, and shortage of emergency commodities.

Table 12: Results for both mono- and bi-objective models.

	Instance	Total Cost	Logistic Cost	Deprivation Cost	Total Shortage	Total unmet demand	First Stage Cost: Operating Cost	First Stage Cost: Rental Cost	Second Stage Cost: Rental Cost	Second Stage Cost: Shipping Cost	Second Stage Cost: Inventory Cost	Second Stage Cost: Meeting Cost
I1	MFLTP	1,884,828,717	172,821	1,884,655,896	24,103	99	16,400	116,080	32,132	1,778	2.182	6,429
	FLTP	1,884,850,099	202,145	1,884,647,954	23,710	99	25,800	121,080	46,335	2,505	–	6,425
I2	MFLTP	414,397,651	48,391	414,349,260	7,062	10	16,400	22,800	1,273	1,431	–	6,487
	FLTP	414,398,026	48,767	414,349,259	7,062	10	16,400	22,960	2,141	779.1	–	6,487
I3	MFLTP	18,438,508,561	44,263	18,438,464,298	21,371	21,370	16,400	22,960	2,904	1,072	–	926.4
	FLTP	18,438,501,902	37,604	18,438,464,298	21,372	21,370	16,400	13,120	6,473	637.1	–	974.6
I4	MFLTP	3,137,684,580	176,638	3,137,507,942	28,813	4,655	47,600	52,480	65,473	5,957	–	5,127
	FLTP	3,137,688,101	184,589	3,137,503,512	28,524	4,655	47,600	54,360	70,878	6,515	–	5,236
I5	MFLTP	1,887,843,215	100,740	1,887,742,475	23,704	99	19,600	54,200	18,555	1,957	–	6,428
	FLTP	1,887,930,347	194,533	1,887,735,814	23,703	99	19,600	121,080	45,282	2,142	–	6,428
I6	MFLTP	59,956,740,838	19,065,161	59,937,675,677	1,982,892	270,956	31,200	5,226,320	12,437,114	1,140,511	14.54	230,001
	FLTP	59,957,040,455	19,373,125	59,937,667,330	1,956,835	270,955	31,200	5,334,560	12,625,185	1,151,892	29.44	230,259
I7	MFLTP	1,884,768,440	113,233	1,884,655,207	23,703	99	22,600	16,400	66,032	1,773	–	6,428
	FLTP	1,884,723,293	68,087	1,884,655,206	23,705	99	16,400	16,400	27,832	1,027	–	6,428
I8	MFLTP	1,885,749,239	831,031	1,884,918,208	23,965	99	22,800	25,000	749,941	26,859	–	6,431
	FLTP	1,885,758,890	841,786	1,884,917,105	23,706	99	22,800	25,000	761,653	25,904	–	6,429
I9	MFLTP	1,203,627,641	3,210,592	1,200,417,049	1,820,480	39	59,600	1,220,160	1,694,820	33,583	–	202,429
	FLTP	1,205,842,758	5,597,819	1,200,244,939	1,816,796	39	65,800	678,960	4,626,988	52,406	0.0000	173,665
I10	MFLTP	242,617,628	1,744,604	240,873,024	352,294	9	42,400	987,280	508,331	38,129	407.4	168,056
	FLTP	243,275,861	2,419,974	240,855,888	351,362	9	62,800	1,134,880	1,013,396	34,686	–	174,211
I11	MFLTP	506,581,341,615	1,489,902	506,579,851,713	1,880,080	1,857,227	52,600	554,320	806,205	33,154	–	43,623
	FLTP	506,581,358,957	1,508,601	506,579,850,357	1,857,244	1,857,227	62,800	574,000	792,462	34,135	–	45,204
I12	MFLTP	766,894,350,945	1,361,377	766,892,989,568	4,355,343	4,249,700	107,200	864,470	332,463	43,252	–	13,992
	FLTP	766,894,324,796	1,413,271	766,892,911,525	4,353,851	4,249,700	107,200	761,350	482,942	46,592	449.0	14,737
I13	MFLTP	1,230,778,630	3,830,323	1,226,948,307	1,866,874	39	59,600	1,964,720	1,562,665	31,783	–	211,555
	FLTP	1,231,782,239	6,634,392	1,225,147,846	1,816,802	39	55,600	2,063,120	4,274,614	46,476	1,912	192,671
I14	MFLTP	1,243,391,298	46,737,290	1,196,654,008	4,061,474	126	76,000	3,947,600	41,783,415	235,575	–	694,699
	FLTP	1,246,543,290	50,084,074	1,196,459,216	3,867,004	126	85,400	4,428,960	44,862,573	213,463	–	493,678
I15	MFLTP	1,203,087,078	2,670,030	1,200,417,049	1,820,480	39	59,600	32,800	2,341,982	33,084	–	202,563
	FLTP	1,203,140,968	2,724,136	1,200,416,831	1,816,802	39	49,400	32,800	2,402,373	35,581	38.31	203,945
I16	MFLTP	1,225,216,157	22,408,672	1,202,807,485	1,817,446	39	43,400	50,000	22,057,821	128,561	449.4	128,441
	FLTP	1,228,670,456	28,343,261	1,200,327,195	1,816,796	39	66,000	50,000	27,919,139	177,426	642.6	130,053
I17	MFLTP	1,288,118,934	79,485,010	1,208,633,924	1,817,332	39	46,400	833,300	78,491,053	67,724	21,296	25,238
	FLTP	1,332,728,583	132,483,645	1,200,244,939	1,816,796	39	72,200	833,300	131,488,548	67,067	–	22,530
Average	MFLTP	80,623,708,892	10,793,534	80,612,915,358	1,289,848	376,744	43,518	940,641	9,585,422	107,422	1,304	115,227
	FLTP	85,255,407,726	14,832,930	80,612,141,130	1,271,886	376,744	48,435	956,819	13,614,636	111,720	180.6	101,139
	MFLTP−FLTP	−4,631,698,834	−4,039,396	774,228	17,962	–	−4,918	−16,179	−4,029,214	−4,297	1,123	14,088

Table 13: Shortage by scenario for both mono- and bi-objective models in instance I14.

Scenario	Model MFLTP	Model FLTP	Difference (MFLTP-FLTP)
Emergency situation	455	455	0
Emergency situation	607	607	0
Crisis situation	769	769	0
Crisis situation	1,058	963	95
Crisis situation	1,030	1,030	0
Crisis situation	1,114	1,109	5
Crisis situation	1,155	1,081	74
Minor situation	22,474	22,474	0
Minor situation	33,210	32,835	375
Moderate disaster	71,472	69,581	1,891
Moderate disaster	154,794	153,482	1,312
Major disaster	1,125,239	934,665	190,574
Major disaster	2,648,098	2,647,953	145
Total	4,061,474	3,867,004	194,470

As expected, there is a clear tradeoff between logistics and deprivation costs. The mono-objective approach yields an average logistics cost 21% lower than the bi-objective model, while deprivation costs are only marginally affected. Cheaper logistics costs were achieved mainly by reducing the corresponding fixed costs. In fact, the first and the second-stage fixed costs of vehicles were decreased by 4 and 55%, respectively, whereas the fixed costs associated with relief centers were 12% cheaper. On the other hand, inventory costs increased up to 9% as a result of extra inventory to take advantage of vehicle capacity.

Not surprisingly, the total unmet demand in the last period is similar in both approaches because deprivation costs incurred in not meeting demand at the end of the time horizon are prohibitively high. On the other hand, the shortage of emergency commodities over the time horizon is almost 1% worse in the mono-objective problem. Although this number could sound negligible in a commercial supply chain, it represents an average of 9,129 emergency aid units that could be sufficient to supply overall demand in many affected areas with a lower number of victims, e.g., São José do Vale do Rio Preto (SJV), which is in line with the spirit of humanitarian logistics. The bi-objective results are particularly appealing for dealing with worse scenarios. For example, according to the results from instance I14, the bi-objective model delivers 190,000 more commodities in comparison to the mono-objective in the case of a major disaster.

The performance of both models is explained as follows. The bi-objective model yields shortages only when there is not sufficient supply and/or capacity to meet demand in the affected areas, as deprivation costs are prioritized in the first level. In the mono-objective model, though, both costs are considered together; for this reason, there is no general preference between either deprivation or logistics costs. In particular, as the shortage cost incurred in postponing one unit of any emergency aid for an hour is lower than the fixed cost of acquiring any vehicle, the mono-objective problem rations supplies that are available at the depots, thus causing "unnecessary" short-term deprivation at some nodes that do not necessarily lead to improved deprivation costs in future periods. Similar results were also pointed out by Pérez-Rodríguez and Holguín-Veras (2015). Thus, the bi-objective model provides a superior solution as it reduces both the deprivation cost and the rationing of commodities.

Finally, it is worth noting that both approaches have similar computational performance. In fact, in the bi-level framework, the first level is solved very fast (on average, 16 seconds, as shown Table 7), while the second level takes 1 hour. The mono-objective approach uses all the time limit of 2 hours to provide a feasible solution. Both approaches require the utilization of the proposed heuristic methods.

5.6. *Expected Value of Perfect Information and Value of the Stochastic Solution*

In order to quantify the uncertainty effect in our problem, we analyzed both the Expected Value of Perfect Information (EVPI) and the Value of the Stochastic Solution (VSS) (Kall and Wallace, 1994; Birge and Louveaux, 1997). Whereas EVPI measures the expected gain of perfect information, VSS represents the expected cost incurred in ignoring uncertainty while making a decision. We evaluate EVPI as follows: EVPI = RP − WS, in which RP is the objective value of the two-stage stochastic programming problem, $\mathrm{WS} = \sum_{\xi} \pi(\xi) \cdot \mathrm{WS}(\xi)$ is the expected wait-and-see solution, and $\mathrm{WS}(\xi)$ expresses the objective value of the deterministic problem for scenario ξ. VSS is posed as follows: VSS = EEV − RP. EEV represents the expected value of using the EV solution, and EV is the expected value problem. EEV exhibits the same structure as the recourse problem, but with the first-stage variables fixed according to a reference scenario given by problem EV. We use the worst-case scenario as our reference EV problem as in Döyen et al. (2011) and Moreno et al. (2016) to avoid underestimating the number of vehicles and relief centers necessary to perform distribution in the most pessimistic scenarios, thus implying excessively high overall costs.

Problems WS, EV, and EEV were solved using the best solution method described in 4. As deprivation costs are similar for all these problems in most instances, we evaluated both EVPI and VSS measures based on the logistics costs only. An exception was given by instances I6 and I8 in which deprivation costs yielded by the EEV problem are much higher than the corresponding deprivation costs provided by the RP problem. Neglecting uncertainty in these case deteriorates significantly the demand fulfillment policy. On average, both EVPI and VSS values are relatively high, suggesting that not only randomness is indeed important, but also that ignoring uncertainty via the worst-case reference scenario leads to a bad strategy. Table 14 summarizes the EVPI and VSS results.

Taking the first-stage decisions based on the worst-case scenario given by the EV problem usually lead to an over pessimistic relief distribution strategy. This is particularly true for instances with a higher number of scenarios (I6) or with a limited number of available vehicles in the first-stage (I8). On instance I8, for example, under the minor disaster scenario (worst-case scenario for that instance), there are many routes that are not available for trucks, which are the only transportation mode in this case. Thus, the distribution of aid to some RCs is not possible, which results in not pre-selecting them. In fact, it is useless to establish a RC if there is no vehicle that may reach it. However, some of those RCs are necessary to the relief distribution and humanitarian assistance in less pessimistic scenarios, which are not taken into account when we solve the EV problem based on the worst-case scenario. As a result, the corresponding EEV solution presents an increased unmet demand in comparison to the RP solution.

Similarly, on instance I6, the configuration of the transportation network based on the worst-case scenario (a major disaster situation) is suitable for performing the relief distribution by boats only. Nevertheless, it turns out to be more expensive or even infeasible to use boats to perform the relief distribution in emergency situation scenarios whose corresponding networks are mainly suitable for land transportation. On the other hand, as instance I14 allows for renting helicopters in the second-stage, it is possible to meet victim's needs via such mode, but this strategy generates higher logistics costs, as expected. In this case, the configuration of the network based on the relief distribution of goods by boats in the worst-case scenario is also suitable for the use of helicopters in the other scenarios. In fact, the transportation network defined in the first-stage according to the EV problem does not affect the demand fulfillment policy, but it increases logistics costs substantially, mainly due to the (first-stage) vehicles' fixed costs and by the (second-stage) shipping and meeting costs. For instances I1-I5 and I9-I14, e.g., the fleet sizing based on the worst-case scenario overestimates the number of vehicles actually needed for the relief distribution, thus increasing the EEV first-stage costs. In addition, some procured vehicles may be unsuitable or useless for less pessimistic scenarios. On the other hand, most vehicles procured in the first-stage of the RP problem are suitable for the majority of its scenarios. Exceptions are noticed in instances I7 and I15-I17 in which the number of available vehicles in the first-stage is not sufficient to perform relief distribution. Therefore, both RP and EEV solutions provide similar first-stage procured costs.

The instances with fewer vehicles in the first-stage (I7, I8, I15, I16, and I17) yield relatively low EVPIs. In fact, in those cases, the first-stage decisions are usually equal to the upper bound on the total number of available vehicles, so both problems WS and RP have similar objective values, which decreases EVPI values. It seems that the impact of the uncertainty is more pronounced in the instances with more scenarios (I6 and I14). Consequently, the cost of ignoring uncertainty is also higher in these instances, as the reference scenario is not a good approximation to the empirical distribution of the random variables. For reduced capacities and/or changes in the available amount of external supply, EVPI and VSS decreased in comparison to the base case (I1 and I9). Finally, higher travel times lead to higher EVPIs, as suggested by the results of instances (I8 and I16).

Table 14: EVPI and VSS values.

	Logistics cost (f^{LC})			
Instance	EVPI	EVPI/RP (%)	VSS	VSS/RP (%)
I1	165,613	81.93	20,596	0.0011
I2	13,779	28.25	37,252	0.0090
I3	9,968	26.51	9,737	0.0001
I4	129,117	69.95	49,316	0.0016
I5	158,026	81.23	28,015	0.0015
I6	13,005,624	67.13	NA	NA
I7	7,274	10.68	17	0.0000
I8	26,330	3.128	NA	NA
I9	3,881,446	69.34	3,215,906	0.2679
I10	2,165,416	89.48	575,605	0.2390
I11	1,394,974	92.47	490,545	0.0001
I12	1,194,517	84.52	644,196	0.0001
I13	4,909,655	74.00	2,789,848	0.2277
I14	42,908,821	85.67	44,546,580	3.723
I15	772,825	28.37	29,955	0.0025
I16	2,493,405	8.797	75,652	0.0063
I17	20,467,264	15.45	704,054	0.0587
Average	5,512,003	53.93	3,547,818	0.3026
Maximum	42,908,821	92.46	44,546,580	3.723
Minimum	7,274	3.127	16.55	–

NA: Not Available.

6. Conclusions and future research

Particularly in under-developed countries, the administrative bodies responsible for disaster management activities struggle to provide a coordinated and effective disaster response due to the complex characteristics of these wrenching events. From the social concerns' point of view, human suffering must be mitigated as much as possible, but overall scarce resources often make this task challenging. We have attempted to deal with this complexity by proposing a novel integrated relief distribution model under uncertainty with deprivation costs via mono- and bi-objective approaches. The proposed optimization model is indeed effective to help in humanitarian relief because we combined several practical decisions regarding the location of relief centers, distribution aspects involving type and number of vehicles before and after the occurrence of a disaster, inventory levels at relief centers, and also the possibility of increasing the coverage of distribution by allowing multiple trips within and over time periods for any vehicle. Deprivation costs account for the amount of time that the victims are deprived from emergency aid. Different aid implies different deprivation times and costs, which may represent the importance of a certain commodity over the remaining ones. Differently from the main literature, the optimization model with deprivation costs is still a mixed-integer linear program − even though the deprivation function preserves the inherent exponential nature of the human suffering −, as deprivation times are treated as inputs of the problem. A potential limitation of the proposed model is its computational efficiency when practical instances are solved only via commercial optimization packages. To overcome this issue, specific mathematical programming based heuristics were designed to solve more efficiently the proposed instances.

From a real set of instances inspired by the so-called Megadisaster of the Serrana region of upstate Rio de Janeiro of 2011, we have showed that deprivation costs may improve not only service levels, but also enhance distribution fairness among the affected areas. In fact, in some cases, service levels were 16.17% better and 21% more equitable. The possibility of performing multiple trips contributed in saving overall resources, thus also improving service levels. It is worth concluding that both the mono- and bi-objective modeling paradigms we devised could be controversial from some points of view. On the one hand, the bi-objective model does not consider logistics cost at the first level, which modifies the original idea of social cost proposed by Holguín-Veras et al. (2013). On the other hand, the mono-objective model rations supplies that are already available at the depots, thus causing "unnecessary" short-term deprivation at some nodes that do not necessarily lead to improved deprivation costs in future periods. Following the humanitarian principles standpoint, we believe that relief aid rationing should be avoided as much as possible if there are enough resources to perform the distribution. In cases where resources are very scarce, on the contrary, rationing of product could be absolutely justified.

In an attempt to make our results indeed useful to help humanitarian logisticians in real disaster situations, it would be necessary to use the mathematical tools within information system frameworks, e.g. GIS technologies, in real-time disaster operations, and/or as a part of training programs (simulation) for professionals that work in the field not only in the aftermath of a disaster, but also prior to disaster. Thus a natural extension of this paper would be to explore the combination of such technologies and optimization models, as in Rodríguez-Espíndola et al. (2018). Consequently, alternative faster solution methods should be fundamental to provide almost online solutions. Due to the unpredictability of the disaster events, minimizing the expected value only may be risky, thus risk-averse two-stage models deserve future investigation, as in . Finally, it might be useful to model deprivation costs based on the severity casualty, so as to penalize with a higher deprivation cost those shortages associated with worse severity levels.

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References

References

Afshar, A., Haghani, A., 2012. Modeling integrated supply chain logistics in real-time large-scale disaster relief operations. Socio-Economic Planning Sciences 46 (4), 327–338.
URL http://linkinghub.elsevier.com/retrieve/pii/S0038012111000644

Ahmadi, M., Seifi, A., Tootooni, B., 2015. A humanitarian logistics model for disaster relief operation considering network failure and standard relief time : A case study on San Francisco district. Transportation Research Part E 75, 145–163.
URL http://dx.doi.org/10.1016/j.tre.2015.01.008

Alem, D., Clark, A., Moreno, A., 2016. Stochastic network models for logistics planning in disaster relief. European Journal of Operational Research 255 (1), 187–206.
URL http://linkinghub.elsevier.com/retrieve/pii/S0377221716302788

Anandalingam, G., Friesz, T. L., 1992. Hierarchical optimization: An introduction. Annals of Operations Research 34 (1), 1–11.

Barber, E., 2012. Military involvement in humanitarian supply chains. In: Kovács, G., Spens, K. M. (Eds.), Relief Supply Chain Management for Disasters: Humanitarian, Aid and Emergency Logistics. Hershey, Pennsylvania, USA: IGI Global, Ch. 8, pp. 123–146.
URL http://www.igi-global.com/book/relief-supply-chain-management-disasters/50516

Bastian, N. D., Griffin, P. M., Spero, E., Fulton, L. V., jun 2016. Multi-criteria logistics modeling for military humanitarian assistance and disaster relief aerial delivery operations. Optimization Letters 10 (5), 921–953.
URL http://dx.doi.org/10.1007/s11590-015-0888-1http://link.springer.com/10.1007/s11590-015-0888-1

Birge, J. R., Louveaux, F., 1997. Introduction to stochastic programming. Springer, New York.

Bozorgi-Amiri, A., Khorsi, M., jul 2016. A dynamic multi-objective location–routing model for relief logistic planning under uncertainty on demand, travel time, and cost parameters. The International Journal of Advanced Manufacturing Technology 85 (5-8), 1633–1648.
URL http://dx.doi.org/10.1007/s00170-015-7923-3http://link.springer.com/10.1007/s00170-015-7923-3

Döyen, A., Aras, N., Barbarosoğlu, G., 2011. A two-echelon stochastic facility location model for humanitarian relief logistics. Optimization Letters 6 (6), 1123–1145.
URL http://link.springer.com/10.1007/s11590-011-0421-0

Dolan, E. D., Moré, J. J., 2002. Benchmarking optimization software with performance profiles. Mathematical Programming 91 (2), 201–213.
URL http://dx.doi.org/10.1007/s101070100263

Dourado, F., Arraes, T. C., Silva, M. F. e., 12 2012. O megadesastre da região Serrana do Rio de Janeiro – as causas do evento, os mecanismos dos movimentos de massa e a distribuição espacial dos investimentos de reconstrução no pós-desastre. Anuário do Instituto de Geociências - UFRJ 35, 43 – 54, in Portuguese.
URL http://dx.doi.org/10.11137/2012_2_43_54

Efron, B., 1979. Bootstrap methods: another look at the Jackknife. The Annals of Statistics 7 (1), 1–26.

EM-DAT, 2015. The international disaster database. Accessed on 01/06/2015.
URL http://www.emdat.be/advanced_search/index.html

Eshghi, K., Larson, R. C., 2008. Disasters: lessons from the past 105 years. Disaster Prevention and Management 17 (1), 62–82.
URL http://www.emeraldinsight.com/10.1108/09653560810855883

Ferrer, J. M., Ortuño, M. T., Tirado, G., 2016. A GRASP metaheuristic for humanitarian aid distribution. Journal of Heuristics 22 (1), 55–87.
URL "http://dx.doi.org/10.1007/s10732-015-9302-5

Galindo, G., Batta, R., 2013. Prepositioning of supplies in preparation for a hurricane under potential destruction of prepositioned supplies. Socio-Economic Planning Sciences 47 (1), 20 – 37.
URL http://www.sciencedirect.com/science/article/pii/S0038012112000596

Haimes, Y., Lasdon, L., Wismer, D., 1971. On a Bicriterion Formulation of the Problems of Integrated System Identification and System Optimization. Systems, Man and Cybernetics, IEEE Transactions on SMC-1 (3), 296–297.

Holguín-Veras, J., Amaya-Leal, J., Cantillo, V., Van Wassenhove, L. N., Aros-Vera, F., Jaller, M., 2016. Econometric estimation of deprivation cost functions: A contingent valuation experiment. Journal of Operations Management.
URL http://linkinghub.elsevier.com/retrieve/pii/S0272696316300420

Holguín-Veras, J., Pérez, N., Jaller, M., Van Wassenhove, L. N., Aros-Vera, F., Jul. 2013. On the appropriate objective function for post-disaster humanitarian logistics models. Journal of Operations Management 31 (5), 262–280.
URL http://linkinghub.elsevier.com/retrieve/pii/S0272696313000417

Huang, K., Jiang, Y., Yuan, Y., Zhao, L., 2015. Modeling multiple humanitarian objectives in emergency response to large-scale disasters. Transportation Research Part E: Logistics and Transportation Review 75, 1–17.
URL http://www.sciencedirect.com/science/article/pii/S136655451400204X

Kall, P., Wallace, S. W., 1994. Stochastic programming. John Wiley & Sons, Chichester.

Lin, Y.-H., Batta, R., Rogerson, P. A., Blatt, A., Flanigan, M., 2011. A logistics model for emergency supply of critical items in the aftermath of a disaster. Socio-Economic Planning Sciences 45 (4), 132 – 145.
URL http://www.sciencedirect.com/science/article/pii/S0038012111000164

Lin, Y.-H., Batta, R., Rogerson, P. A., Blatt, A., Flanigan, M., 2012. Location of temporary depots to facilitate relief operations after an earthquake. Socio-Economic Planning Sciences 46 (2), 112 – 123.
URL http://www.sciencedirect.com/science/article/pii/S003801211200002X

Mete, H. O., Zabinsky, Z. B., 2010. Stochastic optimization of medical supply location and distribution in disaster management. International Journal of Production Economics 126 (1), 76–84.
URL http://linkinghub.elsevier.com/retrieve/pii/S0925527309003582

Moreno, A., Alem, D., Ferreira, D., 2016. Heuristic approaches for the multiperiod location-transportation problem with reuse of vehicles in emergency logistics. Computers and Operations Research 69, 79–96.
URL http://dx.doi.org/10.1016/j.cor.2015.12.002

Moreno, A., Ferreira, D., Alem, D., 2017. A bi-objective model for the location of relief centers and distribution of commodities in disaster response operations. DYNA 84 (200), 356–366.
URL http://dx.doi.org/10.15446/dyna.v84n200.54810

Ozdamar, L., Ekinci, E., Kucukyazici, B., Jul. 2004. Emergency Logistics Planning in Natural Disasters. Annals of Operations Research 129 (1-4), 217–245.
URL http://link.springer.com/10.1023/B:ANOR.0000030690.27939.39

Pérez-Rodríguez, N., Holguín-Veras, J., 2015. Inventory-allocation distribution models for post-disaster humanitarian logistics with explicit consideration of deprivation costs. Transportation Science, 1–25.
URL http://pubsonline.informs.org/doi/10.1287/trsc.2014.0565

Pradhananga, R., Mutlu, F., Pokharel, S., Holguin-Veras, J., Seth, D., 2016. An integrated resource allocation and distribution model for pre-disaster planning. Computers and Industrial Engineering 91, 229–238.
URL http://dx.doi.org/10.1016/j.cie.2015.11.010

Rath, S., Gendreau, M., Gutjahr, W. J., nov 2016. Bi-objective stochastic programming models for determining depot locations in disaster relief operations. International Transactions in Operational Research 23 (6), 997–1023.
URL http://doi.wiley.com/10.1111/itor.12163

Rio De Janeiro, 2011. Resolução Nº 09/2011 da Assembléia Legislativa. In Portuguese.
URL http://www.clarissagarotinho.com.br/arquivos/relatorio_final_31082011.pdf

Rivera-Royero, D., Galindo, G., Yie-Pinedo, R., 2016. A dynamic model for disaster response considering prioritized demand points. Socio-Economic Planning Sciences 55, 59–75.
URL http://dx.doi.org/10.1016/j.seps.2016.07.001

Rodríguez-Espíndola, O., Albores, P., Brewster, C., 2018. Disaster preparedness in humanitarian logistics: A collaborative approach for resource management in floods. European Journal of Operational Research 264 (3), 978 – 993.
URL http://www.sciencedirect.com/science/article/pii/S0377221717300565

Romero, C., 1991. Handbook of Critical Issues in Goal Programming. Elsevier.
URL http://www.sciencedirect.com/science/article/pii/B9780080406619500087

Salmerón, J., Apte, A., 2010. Stochastic optimization for natural disaster asset prepositioning. Production and Operations Management 19 (5), 561–574.
URL http://dx.doi.org/10.1111/j.1937-5956.2009.01119.x

The Sphere Project, 2011. Humanitarian charter and minimum standards in humanitarian response. Belmont Press Ltd, Northampton.
URL http://practicalaction.org/sphere

Valencio, N., 2010. Desastres , Ordem Social e Planejamento em Defesa Civil : o contexto brasileiro. Saúde e Sociedade 19 (4), 748–762.

Vanajakumari, M., Kumar, S., Gupta, S., may 2016. An Integrated Logistic Model for Predictable Disasters. Production and Operations Management 25 (5), 791–811.
URL http://doi.wiley.com/10.1111/poms.12533

Yi, W., Kumar, A., Nov. 2007. Ant colony optimization for disaster relief operations. Transportation Research Part E: Logistics and Transportation Review 43 (6), 660–672.
URL http://linkinghub.elsevier.com/retrieve/pii/S136655450700021X

Yi, W., Ozdamar, L., Jun. 2007. A dynamic logistics coordination model for evacuation and support in disaster response activities. European Journal of Operational Research 179 (3), 1177–1193.
URL http://linkinghub.elsevier.com/retrieve/pii/S0377221706000932

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